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Sabrina Genz
Utrecht University

Terry Gregory
IZA and ZEW Mannheim

Markus Janser
IAB Nueremberg

Florian Lehmer
IAB Nueremberg

Britta Matthes
IAB Nueremberg

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

How Do Workers Adjust When Firms Adopt New Technologies?*

We investigate how workers adjust to firms' investments into new digital technologies, including artificial intelligence, augmented reality, or 3D printing. For this, we collected novel data that links survey information on firms' technology adoption to administrative social security data. We then compare individual outcomes between workers employed at technology adopters relative to non-adopters. Depending on the type of technology, we find evidence for improved employment stability, higher wage growth, and increased cumulative earnings in response to digital technology adoption. These beneficial adjustments seem to be driven by technologies used by service providers rather than manufacturers. However, the adjustments do not occur equally across worker groups: IT-related expert jobs with non-routine analytic tasks benefit most from technological upgrading, coinciding with highly complex job requirements, but not necessarily with more academic skills.

JEL Classification: J23, J31, J62, 033

Keywords: technological change, artificial intelligence, employment stability, wages

Corresponding author:
Terry Gregory
IZA - Institute of Labor Economics
Schaumburg-Lippe-Straße 5–9
53113 Bonn
Germany
E-mail: gregory@iza.org

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1 Introduction

Recent technological developments such as artificial intelligence (AI), augmented reality (AR), or 3D printing have put forward a new generation of technologies that are increasingly connecting the physical and digital spheres to so-called cyber-physical systems. Whereas some have referred to this development as the second machine age (Brynjolfsson and McAfee, 2014), others associate it with the Fourth Industrial Revolution (Schwab, 2017).[1] These new technologies are suspected of having a large impact on the economy (Furman and Seamans, 2019). On the one hand, there are claims suggesting that new technologies may reduce overall employment, sparked by a series of studies predicting that large shares of U.S. and European jobs might be replaced by robots and algorithms (Bowles, 2014; Frey and Osborne, 2017).[2] On the other hand, studies suggest that new technologies such as AI might replace very different parts of the workforce compared to earlier waves of automation (Brynjolfsson et al., 2018; Webb, 2020).[3] Despite these claims, there is hardly any empirical evidence on the adoption and diffusion of new technologies across the economy as well as on the corresponding adjustments of firms and workers. One reason lies in the lack of adequate data on technology adoption, especially at the level of firms (Seamans and Raj, 2018).

This paper adds to this debate by making the following three contributions: First, we build a linked employer-employee data set with information on firms' technology adoption. For this, we conducted a survey among a representative sample of 2,032 German establishments (hereafter referred to as firms) in 2016. The survey sample includes both manufacturers and service providers. The key advantage of the survey compared to existing data sources is that it includes direct measures of firm-level technology adoption in 2016 as well as retrospective information for 2011. In particular, the measure captures firms' investments into three types of work equipment: non-digital 1.0-/2.0-technologies (e.g., older X-rays, fax or copy machines), older digital

[1]The First Industrial Revolution (started around 1800) relates to the transition from hand production to mechanical machines through the use of steam and water power. The Second Industrial Revolution (end of the 19th century) refers to the introduction of mass production and assembly lines enabled by the use of electricity. The Third Industrial Revolution (started in the 1970s) is characterized by automation through electronics and IT and brought forward personal computers.

[2]Research shows that these automation potentials are seriously overstated and neglect, among others, the adaptability of jobs in the digital transformation (Arntz et al., 2017; Autor, 2015). Besides, studies for past waves of automation suggest that job losses due to *actual* automation were overcompensated by job-creation effects, resulting in net positive employment effects from automation (Gregory et al., 2021).

[3]Brynjolfsson et al. (2018) build an occupational measure called "suitability for machine learning" (SML). They show that SML tasks exist in almost all occupations in all industries and further demonstrate that is is weakly correlated with wage and wage bill percentiles. Webb (2020) predicts that AI will much more likely affect highly-educated and older workers compared to previous technologies.

3.0-technologies (e.g., computers, CNC machines, or industrial robots) and more recent digital and connected 4.0-technologies (e.g., AI, AR, or 3D printing). We link the survey data to administrative employment data records of the 172,714 workers employed in 2011 in the surveyed firms. This way, we can track the entire individual employment and wage history across the universe of German firms in the aftermath of firms' technology investments. With this novel data, we first provide basic descriptive statistics on technology adoption in Germany. Accordingly, modern 4.0-technologies still play a relatively minor role in firms across the economy. Between 2011 and 2016, we find that 29% of German firms invested mainly in non-digital technologies (referred to as non-adopters), 49% in 3.0-technologies (3.0-adopters), and 22% invested primarily in 4.0-technologies (4.0-adopters). The group of 4.0-adopters constitutes a sizable number of firms at the technological frontier that either already use connected 4.0-technologies to a considerable extent or have recently invested heavily in them. Since 2011, the average share of 4.0-technologies rose by 11pp among 4.0-adopters, such that they made up 23% of the entire work equipment in 2016. We further show that technology adopters (both 3.0- and 4.0-adopters) tend to attract a positive selection of workers. In 2011, workers in adopting firms were more qualified, performed more complex tasks, received higher wages, and experienced more stable employment biographies (e.g., measured by the number of days employed) relative to non-adopters, i.e., those investing in older non-digital 1.0-/2.0-technologies.

As a second contribution, we investigate adjustments of worker-level outcomes in response to firms' technology investments, including workers' accumulated number of days employed, daily wage growth, and cumulative earnings. We compare these worker-level outcomes between workers from adopting and non-adopting firms during a five-year time span, isolating differences that are driven by other individual- and firm-specific covariates. We thereby distinguish between workers that stay at the initial firm, switch to other firms, or become unemployed (or other non-employment states). Overall, we find significantly increased employment stability, wage growth, and cumulative earnings in response to technology adoption for workers remaining employed at adopting firms. However, the gains differ by technology: while 3.0-adoption leads to a significant increase in employment days that translates into higher cumulative labor earnings, 4.0-adoption predominantly results in significantly stronger wage growth without corresponding adjustments in employment stability and earnings. Moreover, these beneficial adjustments seem to be driven by technologies used by service providers rather than manufacturers. We further find that the adjustments do not occur equally across worker groups. Our results by occupational fields, jobs requirements, tasks, and education indicate that IT-related jobs (that require substantially more programming skills) benefit most from technological upgrading. Accordingly, workers conducting highly complex job requirements, non-routine analytic tasks, and workers with vocational training (rather than university) degrees experience enhanced labor market performance.

As a third contribution, we exploit how chances to be hired in adopters relative to non-adopters depends on workers' characteristics, including age, occupational fields, job requirements, and education. We thereby distinguish between 117,450 individuals entering 3.0- and 4.0-adopters relative to non-adopters. By including such an analysis at the hiring margin, we provide a more comprehensive picture of worker adjustments to new technologies in Germany. The analysis points towards adjustments similar to the analysis for incumbent workers: investments in new technologies shift labor demand towards IT occupations with highly complex work tasks. However, these shifts are more pronounced among 4.0-adopters than 3.0-adopters and favor particularly younger workers' hiring probabilities and those of business services jobs (speaking for business expansions).

This paper, thereby, contributes to several strands of the literature. First, we contribute to the emerging literature focusing on firm-level technology adoption. This literature focuses primarily on indirect measures of automation or robot adoption. Accordingly, robot adoption generates substantial output and employment gains as well as reductions in the labor cost share, compared to non-adopting firms (Acemoglu et al., 2020; Koch et al., 2021). Further evidence suggests that robot adoption leads to higher wages. However, wage increases are limited to skilled workers such as computer analysts, engineers, and researchers while being negative for production workers (Humlum, 2019). One of the few studies focusing on what happens to individual workers when their firm decides to automate is Bessen et al. (2019). The authors exploit information on firms' expenditures on third-party automation, suggesting that firm-level automation increases incumbent workers' probability to separate from their employer, followed by wage income losses that are only partly offset by social benefits. We add to this literature by using a direct firm-level technology measure that distinguishes between older digital 3.0-technologies and most recent 4.0-technologies and allows us to capture technology adoption for both manufacturing and service firms. Furthermore, we observe detailed individual-level information, such as workers' occupation and formal education, allowing us to analyze the heterogeneity in the adjustments for newly entering and incumbent workers in more detail.[4]

[4]For instance, Bessen et al. (2019) do not observe workers' occupation or education in their data.

We also contribute to a related literature strand that provides more indirect evidence for worker adjustments to regional- or industry-wide adoption of automation technologies.[5] For instance, Acemoglu and Restrepo (2020) document negative employment and wage effects of robots in U.S. local labor markets between 1993 and 2007. The displacement effects are most pronounced in manufacturing industries and among routine manual, blue-collar workers. In contrast, Dauth et al. (2021b) look at workers' exposure to industry-wide robot adoption in Germany between 1994 and 2014 and find no aggregate employment effects, as job losses in manufacturing industries are offset by additional jobs in service industries. According to their findings, the reallocation effect stems from incumbent workers taking over new tasks at their employers and young workers entering the labor market, especially in high-skilled service jobs. Moreover, Graetz and Michaels (2018) exploit country-industry variation in robot adoption and find that increasing robot use leads to higher labor productivity growth without significant employment losses, despite lower demand for low-educated workers. In contrast to our study, these studies focus on specific manufacturing-related technologies (industrial robots) and measure technology adoption at the aggregate level (industry or region), allowing only indirect conclusions about what happens to workers when firms adopt new technologies.

The paper is structured as follows. Section 2 describes the firm survey and individual-level administrative social security data. Section 3 defines our direct technology adoption measure, describes how widespread digital technologies are in Germany, and characterizes workers of adopting and non-adopting firms. In Section 4, we discuss the empirical approach, present the results for employment stability and wage growth, and show corresponding robustness checks. In Section 5, we discuss the heterogeneity of the adjustments for different worker groups. Section 6 examines adjustments to technology adoption at the hiring margin. Finally, Section 7 concludes.

2 Data

For our analysis, we built a novel linked employer-employee data set from two main data sources, including (1) a representative firm survey on technology adoption and (2) employment biographies from social security records for all workers employed in the interviewed firms. The following paragraphs describe the data sources in detail.

[5] This literature is also related to studies that look at individual adjustments to trade shocks. For instance, Autor et al. (2014) find significant earnings losses and job destruction for U.S. workers exposed to import competition. Furthermore, Dauth et al. (2021a) find that trade exposure leads to earnings gains for high-skilled workers at the expense of wage losses for low-skilled workers.

2.1 Firm Survey on Technology Adoption

To identify technologies of the Fourth Industrial Revolution, we conducted a representative survey among German establishments (referred to as firms) between March and May 2016 ("IAB-ZEW Labor Market 4.0 Establishment Survey").[6] In particular, we collected information on the recent adoption of cutting-edge automation technologies among 2,032 German firms, including both manufacturers and service providers. The firm survey was conducted based on a random sample of all German firms registered at the German Federal Employment Agency. The survey was stratified by sector, firm size, and location (Appendix Subsection A.1.1 contains more details on the execution of the firm survey). To correct for over- and under-sampling, we weight the observations in our estimations with the inverse probability of being in a specific stratification cell of the survey sample (hereafter referred to as firm stratification weights).

Following written invitations, firms were called to conduct a CATI interview with either the firms' production or general manager. Among all called firms, 2,032 firms completed the interview, which corresponds to a response rate of 31.5% (see Appendix Table 9). Among firms that did not participate in the survey, the large majority did so for reasons unrelated to digital technologies (see Appendix Table 10). Thus, any potential bias concerning the use of technologies should be small. In fact, Appendix Table 11 provides further evidence that the surveyed firms are representative for the entire German firm population. On average, the interviews lasted 30 minutes and covered questions about (1) the relevance and perception of cutting-edge 4.0-technologies, (2) the technology level of a firm's work equipment, (3) changes in firm labor demand regarding skills and competencies as well as (4) background characteristics including sales and profits. The information was gathered for the survey year 2016 as well as retrospective assessments for 2011.

As a unique feature of the survey, it includes a measure of the technological level of firms' work equipment. The aim was to obtain a classification of firms' work equipment by technology levels following the concept of the four industrial revolutions (see footnote 1 for details), i.e., rising in the degree of automation and digitalization (connectivity). Moreover, the technology levels were supposed to be as general and comparable as possible across firms, while at the same time suitable for giving specific technology examples during the interview. Therefore, we distinguished between office and communication (O&C) and production equipment (Prod).[7]

[6] The data can be accessed at the Research Data Center (FDZ) of the German Federal Employment Agency at the Institute for Employment Research (see http://fdz.iab.de).

[7] Firms that do not have production equipment were asked to assess only the technology level of their office

Table 1: Firms' Work Equipment by Technology Level

Technology level (industrial revolutions)	Office and communication equipment ($k_s^{O\&C}$)	Production equipment (k_s^{Prod})
4.0 (4th Industrial Revolution, i.e., 2nd Digital Revolution) Technology performs work progress automatically and autonomously	**IT-integrated** ($k_{4.0}^{O\&C}$) e.g., analytic tools for big data, cloud computing system, or internet platforms	**Self-controlled** ($k_{4.0}^{Prod}$) e.g., production facilities up to smart factory, cyber-physical system, or internet of things
3.0 (3rd Industrial Revolution, i.e., 1st Digital Revolution) Humans are indirectly involved in work process	**IT-supported** ($k_{3.0}^{O\&C}$) e.g., computer, CAD-system, or electronic checkout system	**Indirectly controlled** ($k_{3.0}^{Prod}$) e.g., CNC machine, industrial robots, or process engineering system
1.0/2.0 (1st/2nd Industrial Revolution, i.e., before Digital Revolution) Humans manually conduct work process	**Not IT-supported** ($k_{1.0/2.0}^{O\&C}$) e.g., telephone, fax, or copy machine	**Manually controlled** ($k_{1.0/2.0}^{Prod}$) e.g., drilling machine, motor vehicle, or X-ray machine

Notes: The table shows the technology levels as they were explained to the interviewees during the CATI-interview. The interviewees were then asked to give an estimate of how their work equipment is divided across these technology levels (in percent). Technology levels refer to the concept of the four industrial revolutions as outlined in footnote 1.

Table 1 shows the definition of the technology levels and lists examples for typical work tools. The lowest level of 1.0-/2.0-technologies refers to technologies from the First and Second Industrial Revolution (before the Digital Revolution). These include not IT-supported office and communication equipment (e.g., an analog telephone or copy machine) and manually controlled production machines (e.g., a drilling machine). The level of 3.0-technologies reflects technologies introduced in the Third Industrial Revolution (First Digital Revolution), which differ from earlier technologies as they are for the first time supported by IT and enable automating specific sub-processes. This category consists of IT-supported office and communication equipment (e.g., a personal computer) and indirectly controlled production equipment (e.g., a CNC machine or industrial robots). The highest level of 4.0-technologies is related to the Fourth Industrial Revolution (Second Digital Revolution) that are self-controlled and fully integrated into the firm's central IT system. Work equipment belonging to this category performs the work progress autonomously without any need for human intervention. We consider IT-integrated office and communication equipment (e.g., cloud computing systems or online platforms) and self-controlled

and communication equipment. All other firms were asked to separately assess the technology level for their office and communication and production equipment.

production equipment (e.g., smart factories or cyber-physical systems) as 4.0-technologies.

Overall, we receive firms' technology-specific work equipment shares separately for office and communication (O&C) and production equipment (Prod) for the years 2011 and 2016. The shares are subjective measures potentially reflecting the number, cost and frequency of the use of each technology relative to the entire stock of work tools. These technology shares are the core of our firm-level technology adoption measure (see Subsection 3.1 for specific details).

From the 2,032 firms, we keep for our analysis only those firms with at least one employee employed subject to social security contributions in regular employment on June 30, 2011. By construction, this restricts the sample to firms that have existed in 2011 (i.e., excluding firms that are founded after June 30, 2011), which leaves us with 1,712 firms.

2.2 Employment Biographies of Workers Employed at the Surveyed Firms

Information on surveyed firms' employees stems from the social security records Integrated Employment Biographies (IEB V13.01.01–190111) provided by the Institute for Employment Research (IAB). The IEB covers the universe of German employees liable to social security contributions, benefit recipients, unemployed searching for employment, and participants in active labor market policy measures, thus excluding self-employed, civil servants, and students. The data contains the complete employment and benefit recipient history of workers on a daily basis. We extract the employment records on June 30th of any year between 2011 and 2016 of all individuals employed in any of the surveyed firms.

To avoid problems due to early retirement, we focus on workers between 18 and 60 years. Moreover, we restrict our sample to workers in regular employment, i.e., excluding apprentices, trainees, and working students. In case of multiple employment, we focus on persons' primary employment. We are thus left with 172,714 individuals that are employed on June 30, 2011 in one of the surveyed firms and 117,450 individuals who enter those firms during the observation period until June 30, 2016. Altogether, the sample contains 290,164 individuals for whom we observe annual information on important characteristics, including gender, age, qualification, employment status, occupation, industry, and daily wage, together with a firm identifier. The administrative employment data includes information on whether individuals conduct full- or part-time jobs, although missing exact working time hours. To avoid bias due to imprecise information on working time, we restrict our wage analysis to full-time workers.

To account for inconsistencies or missing data concerning workers' formal education, we apply a basic version of the approach proposed by Fitzenberger et al. (2006). Exploiting the longitudinal structure of the employment data, we impute the information concerning education according to the information available in preceding or subsequent spells of the individuals' employment history. We follow the approach of Dustmann et al. (2009) and code remaining 2% missing information as the lowest skilled group. Since 13.6% of our individual wage observations are top-coded in our data, we follow Dustmann et al. (2009) and Card et al. (2013) and impute wages above the censoring threshold with wages predicted from censored regressions for each year and by gender.[8] Wages are deflated to 2010 prices.

Throughout our analysis, we control at the firm-level for four firm size categories (0-9, 10-49, 50-199, 200 and more employees), five sector categories (non-knowledge intensive production, knowledge intensive production, non-knowledge intensive service, knowledge intensive service and ICT, see Appendix Subsection A.1.2), and the 16 German federal states. At the individual-level we control for gender, year of birth, foreigner status (German or non-German nationality), four firm tenure categories (0-1, 2-4, 5-9, 10 and more years), and two employment history characteristics (number of previous employers and share of previous days employed). We distinguish our analysis by three educational categories (without vocational training, with vocational training, with university degree), five occupational fields (production, personal services, business services, IT, commercial services, see Appendix Subsection A.1.3 for details on the definition and statistics on the composition), five main task categories (non-routine analytic, non-routine interactive, routine cognitive, routine manual or non-routine manual analog to Autor et al., 2003)[9] as well as four job requirement categories (helpers/assistants, skilled employees, specialists and experts).[10]

[8] As individual covariates, we include age, education (3 categories), foreigner status, tenure, occupational segments (14 categories) and information on the previous labor market history of individuals (number of previous employers and employment share since entrance in the labor market). As firm covariates, we include firm size, firm age, urban area of workplace (4 categories), workplace location (16 German federal states), and economic sector (18 categories).

[9] The main occupational task information stems from the German expert database BERUFENET. See Dengler et al. (2014) for details on the operationalization.

[10] For this we use the fifth digit of occupational code based on the German classification of occupations *KldB 2010* that distinguishes occupations across the following job requirement levels: (1) unskilled or semi-skilled tasks (helpers/assistants), (2) professionally oriented work tasks (skilled employees), (3) complex specialist tasks (specialists) and (4) highly complex work tasks (experts).

3 Technology Adoption

3.1 Defining Technology Adoption

Based on the linked employer-employee data, we calculate firm j's share of work equipment across three technology levels $s \in \{1.0/2.0, 3.0, 4.0\}$ at time t as follows:

$$k_{jst} = \Big((1 - \delta_j)k_{jst}^{O\&C} + \delta_j k_{jst}^{Prod}\Big) \tag{1}$$

where we weight the surveyed office and communication equipment share $k_{jst}^{O\&C}$ and the production equipment share k_{jst}^{Prod} with firms' time-constant initial-level share of blue-collar workers δ_j.[11] We fix δ_j at its initial value in 2011 to ensure that it does not reflect any (endogenous) firm adjustments in response to technology adoption. In Subsection 4.3, we show that our results are robust to an alternative measure for δ_j. Technology shares k_{jst} add up to unity within each firm and year.

To identify firms' technology adoption, we exploit the time variation in the technology shares between 2011 and 2016, i.e., $\Delta k_{js} = k_{jst=2016} - k_{jst=2011}$. In particular, we classify a firm as s-adopter if: (1) the firm increases its share of s-technologies more than the other shares, or (2) s-technologies already made up the highest share of technologies in 2011, conditional on unchanged technology shares between 2011 and 2016. If two technology classes are equally dominant under condition (1) or (2), the highest technology level determines the adoption status (see Appendix Section A.2). This way, we consider both changes in the technology level over time and initial technology levels. Our classification thus distinguishes between three types of firms: adopters of non-digital 1.0-/2.0-technologies (1.0-/2.0-adopters, henceforth referred to as non-adopters), older digital 3.0-technologies (3.0-adopters) and more recent digital and connected 4.0-technologies (4.0-adopters). In our analyses, we conduct an additional estimation, where we define technology adoption separately for service firms and manufacturers (see Subsection 4.3).

3.2 How Widespread Are New Technologies Across the Economy?

Table 2 shows the average technology shares, both in levels and changes between 2011 and 2016, for adopters (either 3.0-adopters and 4.0-adopters) and non-adopters. Overall, the picture is heterogeneous concerning the use of newer and older technologies: 293 non-adopters still mainly

[11] The classification is based on the distinction at the 1-digit level of the International Standard Classification of Occupations 2008 between white-collar (ISCO codes 1 to 5) and blue-collar (ISCO codes 6 to 9) occupations.

use non-digital 1.0-/2.0-technologies – such tools accounted for 86% of all tools in these firms in 2011. Non-adopters also have not invested in modern technologies recently. In fact, they even further reduced their already small share of modern technologies until 2016. In adopting firms, 3.0- and 4.0-technologies together already made up more than half of all tools in 2011, and their shares have further increased between 2011 and 2016.

Table 2: Technology Level of Work Equipment by Adopters vs. Non-Adopters

	Non-adopters (1)	3.0-adopters (2)	4.0-adopters (3)
In 2011:			
Technology share $k_{js}^{t=2011}$ (in %):			
4.0-technology	3.10	3.56	12.46
3.0-technology	10.85	51.04	43.80
1.0/2.0-technology	86.05	45.40	43.74
In 2016:			
Technology share $k_{js}^{t=2016}$ (in %):			
4.0-technology	1.00	3.76	23.08
3.0-technology	10.37	61.43	43.10
1.0/2.0-technology	88.63	34.81	33.82
Change between 2011 and 2016:			
Technology share Δk_{js} (in %):			
4.0-technology	-2.09	0.20	10.62
3.0-technology	-0.48	10.39	-0.70
1.0/2.0-technology	2.58	-10.59	-9.92
Share of all German firms (weighted)	29%	49%	22%
No. of firms	293	907	512

Notes: The figures represent average values across firms and are weighted with firm stratification weights.

However, 3.0- and 4.0-adopters differ in the degree to which they use or invest in digital technologies. A total of 907 firms are classified as 3.0-adopters: their share of 3.0-technologies accounted for 51% of all work tools in 2011 and increased to 61% in 2016. More than one out of five firms (512 firms) predominantly invested into more recent digital 4.0-technologies and are therefore referred to as 4.0-adopters. In 2011, these firms already used by far the largest share (about 13%) of 4.0-technologies among all firms. Until 2016, this share almost doubled to 23%.

Altogether, the group of 4.0-adopters represents firms at the technological frontier that, on average, either already used to a considerable extent or recently invested strongly in connected 4.0-technologies. In contrast, modern 4.0-technologies still play a relatively minor role across most German firms, as judged by the average share of such technologies among the entire stock of work equipment.

3.3 Do Workers Differ Between Technology Adopters and Non-Adopters?

Technology adopters and non-adopters differ in terms of workplaces and personnel. To shed light on such differences, Table 3 compares initial period worker characteristics between workers from non-adopters and adopters.

Table 3: Characteristics of Workers Employed at Technology Adopters vs. Non-Adopters

Worker characteristics in 2011:	Non-adopters (1)	3.0-adopters (2)	*Diff* (2)-(1) (3)	4.0-adopters (4)	*Diff* (4)-(1) (5)
Female share	37.68	51.66	13.97***	45.62	7.93***
Age	41.00	42.24	1.24***	41.39	0.39
Daily wage (in euros)	71.76	85.21	13.45***	89.82	18.06***
Blue-collar worker share	49.21	27.55	-21.66***	26.49	-22.73***
Share of workers by occupational fields (in %):					
Production	37.59	25.86	-11.73***	28.46	-9.13***
Personal services	27.24	27.94	0.69	20.00	-7.24***
Business services	17.58	32.76	15.18***	37.67	20.09***
IT	1.34	2.37	1.03	4.07	2.73***
Commercial services	16.24	11.07	-5.17***	9.80	-6.45***
Share of workers by job requirements (in %):					
Helper/assistant	16.00	9.36	-6.64***	11.54	-4.46***
Skilled employee	66.04	65.90	-0.14	60.57	-5.47**
Specialist	6.53	11.58	5.04***	15.06	8.53***
Expert	11.43	13.16	1.73	12.83	1.40
Share of workers by education (in %):					
No vocational training	11.86	7.44	-4.42***	8.15	-3.71***
Vocational training	80.10	75.72	-4.39***	73.67	-6.43***
University degree	8.04	16.84	8.80***	18.18	10.14***
Share of workers by tasks (in %):					
Non-routine analytic	16.70	22.94	6.24***	24.30	7.60***
Non-routine interactive	4.46	7.51	3.05***	8.66	4.20***
Routine cognitive	22.78	32.77	9.99***	36.02	13.23***
Routine manual	14.18	13.08	-1.10	13.77	-0.40
Non-routine manual	41.88	23.70	-18.18***	17.25	-24.63***
Employment history since 1999:					
Number of employers	3.64	2.41	-1.23***	2.52	-1.12***
Share days employed	84.72	88.36	3.65***	87.29	2.58***
Share of all workers in Germany (weighted)	18%	52%		30%	
No. of individuals	14,869	89,581		68,264	

Notes: The figures represent average values across firms and are weighted with firm stratification weights. Columns (3) and (5) show significance levels from mean comparisons of workers in adopting firms to non-adopters (Column 1) based on t-tests. Significance levels: * 10%, ** 5%, *** 1%.

From the 172,714 workers that we observe on June 30, 2011 in our data, the gross of workers (about half) are employed at 3.0-adopters, with the remaining half split between non-adopters (about 2 in 5) and 4.0-adopters (about 3 in 5). The descriptive comparison based on initial period (in 2011) characteristics suggests that workers from adopting firms significantly differ from those at non-adopters. In general, workers from adopters, either 3.0- and 4.0-adopters, are significantly more often female and white-collar workers with higher daily wages. Moreover, they are more often business service workers (and less often production and commercial service workers), which goes along with a higher share of workers conducting cognitive tasks and a lower share of workers performing non-routine manual tasks. Adopting firms require relatively more specialists (at the expense of helpers) and a significant higher share of university graduates (at the expense of workers with or without vocational training). Workers employed at adopting firms have also experienced relatively more stable employment biographies, measured by the number of employers and the share of days employed (since 1999).

Apart from this, there are more nuanced differences between 3.0- and 4.0-adopters. Whereas 3.0-adopters employ significantly more older workers, relative to non-adopters, 4.0-adopters do not. Also, the higher share of IT-workers and workers in business services is more pronounced among 4.0-adopters (while the share of personal service workers is even lower than in non-adopters). This coincides with a even higher shares of university graduates and specialists and less skilled employees in 4.0-adopters.

Altogether this suggests a more favorable selection of workers in adopting firms relative to non-adopters concerning characteristics that can explain higher individual employment and wage outcomes. To control for such differences, we include a large set of individual- and firm-level covariates in our empirical estimation approach.

4 Worker Adjustments to Firm-Level Technology Adoption

4.1 Empirical Approach

In the following, we aim to shed light on how workers adjust to firms' technology investments, focusing on individual employment, wages and cumulative earnings. For this, we estimate adjustments in worker outcomes in response to firm-level technology investments during the five-year time period by comparing workers from adopter firms to workers from non-adopter firms as follows:

$$Y_i \quad = \quad \alpha + \beta adopter_j^{3.0} + \gamma adopter_j^{4.0} + \delta X_{ij_0} + \varepsilon_i \tag{2}$$

where Y_i represents our outcome variable – such as changes in wages (see discussion of outcomes below) – of individual i in firm j. The terms $adopter_j^{3.0}$ and $adopter_j^{4.0}$ represent our treatment variables that take the value one if workers are employed in 3.0-adopting or 4.0-adopting firms (see Subsection 3.1 for corresponding definitions). β and γ measure how our outcome variables adjust in response to firms' investments into either 3.0- or 4.0-technologies relative to non-adopters. The vector X_{ij_0} represents a set of initial period individual- and firm-level characteristics. We include the individual characteristics gender, year of birth, education (3 categories), tenure (4 categories), and foreigner status as well as the number of previous employers and the share of days employed (both since 1999) to capture the employment history of a worker. At the firm-level, we include firm size (4 categories), sector (5 categories) as well as federal state (16 categories), see Subsection 2.2 for details on the variable categories. To account for serial correlation, we cluster standard errors on the firm level. Finally, we weight the figures with the firm stratification weights to correct for over- and under-sampling in the survey.

Outcomes and Samples. Regarding individual-level outcomes, we focus on employment stability, wages and earnings. For the employment analysis, we focus on the sample of individuals that were employed on June 30 in 2011 and distinguish three types of outcomes: (1) the accumulated number of days employed at the original employer, (2) the accumulated number of days employed at different employers as well as (3) accumulated number of unemployment days (which we distinguish from being out of labor force or irregularly employed, as demonstrated in Appendix Table 16).[12] In a robustness check in Subsection 4.3, we document that the results are robust to estimating the probabilities to remain employed at the original employer, switch to another firm or become unemployed, based on a logit model.

In the case of wages, we look at changes in log daily wages between 2011 and 2016, distinguishing between workers who (1) remain employed at the original firm (stayers) and (2) those who leave the original firm to take up employment at a different employer (switchers). We restrict our wage analysis to full-time workers who earn more than the marginal job threshold. Since wage outcomes are only available for employed workers, the wage sample consists of workers employed on June 30 in 2011 and 2016 (either at the original or a different employer). Thus, those individuals that are not regularly employed anymore on June 30 in 2016, are included in

[12]Irregular employment includes marginal employment, apprentices, and partial-retirement contract workers. Out of labor force refers to the economically inactive population and includes employment states not registered in the administrative social security data.

the employment analysis but not regarded in the wage analysis. To shed more light on the disparities between the two samples, we investigate differences between the three adoption groups among individuals that are no longer employed after five years in Appendix Table 15. By and large, individuals that are not regularly employed on June 30 in 2016 but who worked previously at adopting firms are a positive selection of individuals compared to individuals of non-adopters as judged by the previous job characteristics. This aligns with the more favorable selection of workers in adopting firms as described in Table 3. Finally, we investigate in Subsection 4.3 whether wage changes translate into earnings gains or losses by examining the labor earnings over the five-year period from 2011 to 2016.

Interpretation. We aim to provide first insights into worker adjustments in response to firm-level technology adoption without necessarily ensuring causality. In the following, we discuss to what extent our estimates might still be deviating from the causal effect of firms' technology investments on worker outcomes.

First, it might be that workers differently select into firms with different adoption statuses. For instance, high-skilled workers who quickly adapt to new demands and changing work environments might select disproportionately into investing firms (as suggested by the highest share of university graduates among 4.0-adopters in Table 3). As high-skilled workers and experts generally experience high labor force attachment, we might have observed higher employment stability even in the absence of technology adoption. The large set of covariates at the individual- and firm-level, described in Subsection 2.2, controls for such worker selection and general level differences between firms. Any remaining unobserved characteristics could still lead to deviations from the causal effect of technology adoption. However, additional tests suggest that the influence of remaining unobserved factors is small after controlling for detailed individual-level characteristics.[13]

Second, we assume that changes in firm-level technology adoption are exogenous to changes in individual outcomes. This assumption might be violated if modern technology investments rely on endogenous firm factors, such as management's technology affinity, which correlate at the same time with changes in individual labor market outcomes. Although our rich set of

[13]As a robustness check, we exploit annual observations of the data and repeat the wage growth analysis by estimating regressions including individual fixed effects. Appendix Table 19 confirms our main wage growth results displayed in Table 5, which indicates that any potential remaining unobserved heterogeneity between workers has only a minor influence on the results. Since our employment outcome is not time-varying, we can not perform analogous checks for our employment analysis.

firm-controls presumably captures much of such endogenous variations, we cannot entirely rule out that our estimates deviate from the causal effect.

4.2 Results

4.2.1 Employment Stability

Table 4 shows the results for the three main employment stability outcomes: workers' accumulated number of days employed at the original employer, employed at different employers and unemployed. For each outcome, we estimate a simple ordinary least squares model (OLS) based on the individual cross-sectional data (Columns 1, 4, and 7), a version with individual-level controls (Columns 2, 5, and 8), and with both individual- and firm-level controls (Columns 3, 6, and 9). Panel A gives the estimates for the entire sample, Panel B displays the results from individuals initially employed at service providers, and Panel C those from manufacturers.

Our result in Panel A demonstrates that firm investments into 3.0-technologies statistically significantly increase the average number of accumulated days employed at the original employer by 135 days (Column 1), relative to workers of non-adopters. The result is robust to the inclusion of individual- and firm-level controls, despite reducing the magnitude of the estimate to 63 days (Column 3). In contrast, the positive coefficients for investments into 4.0-technologies are much smaller and insignificant throughout different specifications. The general differences between Columns (1)-(3) suggests that part of the positive association between technology adoption and individuals' employment stability in the raw data is driven by a more favorable selection of workers into technology adopters that we described in Subsection 3.3.

Looking at the results regarding the days employed at different employers (other than the original employer) between 2011 and 2016 (Columns 4-6), we do not find any statistically significant adjustments. All coefficients are negative for workers initially employed at 3.0-adopters, but insignificant. For workers of 4.0-adopters, the coefficient is also negative and insignificant in the baseline specification (Column 4), although the sign turns positive after additionally controlling for individual (Column 5) and firm characteristics (Column 6).

We do not find evidence that technology investments increase the number of days unemployed. For workers initially employed at 3.0-adopters, the coefficient is statistically significantly negative (Column 7) but becomes smaller after controlling for individual-level covariates (Column 8) and turns insignificant after adding firm-level controls (Column 9). For workers originally

Table 4: Adjustments in Workers' Employment Stability to Firms' Technology Investments

Dependent variable: number of accumulated days (after five years)..	..employed at original employer			..employed at different employer			..unemployed		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
A. All Firms (N=172,714)									
3.0-adopters	135.49**	62.55**	62.81**	-53.04	-9.84	-13.84	-33.07***	-15.48**	-11.74
	(2.55)	(2.12)	(2.10)	(-1.63)	(-0.43)	(-0.60)	(-3.53)	(-2.11)	(-1.50)
4.0-adopters	75.50	18.66	21.08	-11.99	16.84	10.38	-14.46	0.15	2.86
	(1.33)	(0.56)	(0.64)	(-0.32)	(0.60)	(0.36)	(-1.21)	(0.02)	(0.25)
B. Service Providers (N=98,482)									
3.0-adopters	136.95**	49.44	62.94*	-51.82	2.83	-12.87	-34.16***	-13.23	-8.81
	(2.11)	(1.42)	(1.79)	(-1.31)	(0.10)	(-0.46)	(-3.02)	(-1.51)	(-0.95)
4.0-adopters	52.11	-0.76	18.53	12.47	40.19	21.69	-11.63	3.20	5.76
	(0.74)	(-0.02)	(0.47)	(0.27)	(1.18)	(0.62)	(-0.79)	(0.28)	(0.44)
C. Manufacturers (N=74,232)									
3.0-adopters	129.72***	96.59***	38.67	-58.06*	-42.63	-22.62	-28.66**	-21.18**	-10.48
	(3.30)	(2.67)	(1.15)	(-1.75)	(-1.45)	(-0.75)	(-2.35)	(-2.15)	(-1.02)
4.0-adopters	141.24***	87.11**	26.68	-87.02***	-59.87**	-35.82	-22.82*	-9.71	-1.45
	(3.51)	(2.31)	(0.73)	(-2.67)	(-2.03)	(-1.14)	(-1.77)	(-0.92)	(-0.13)
Ind. cov.		✓	✓		✓	✓		✓	✓
Firm cov.			✓			✓			✓

Notes: All models are estimated with OLS based on the cross-sectional data and weighted with firm stratification weights. Subsection 4.1 describes the individual- and firm-level covariates. Robust standard errors are clustered at the firm level. t-statistics in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

employed at 4.0-adopters, the correlation is also negative (Column 7) and becomes increasingly positive after adding individual- (Column 8) and firm-level controls (Column 9), while remaining insignificant. Altogether, this suggests that worker selection explains much of the negative correlation between firms' technology adoption and individuals' days spent in unemployment observed in the raw data. In particular, workers with generally fewer days unemployed select into adopter firms. An additional analysis displayed in Appendix Table 16 demonstrates that technology adoption does not push individuals into other unfavorable labor market states such as irregular employment contracts or dropping out of the labor force.

The positive adjustments in workers' employment stability to 3.0-adoption are mainly driven by service providers. In particular, the results of Panel B in Table 4 demonstrate positive employment responses for workers originally employed at service providers that are similar in magnitude compared to Panel A, albeit less significant. In contrast, the magnitude of the coefficient including individual- and firm-level covariates for workers of manufacturers (Panel C Column 3) is only halve as large and insignificant. Turning to the accumulated days employed at different employers, workers of 4.0-adopting manufacturers experience even less days employed at other firms compared to workers of non-adopters (Panel C Column 6), whereas workers of 4.0-adopting service providers accumulate more days employed at other employers (Panel B Column 6), albeit both differences are not significant. Taken together, these results yield a first indication that digital technology adoption is more beneficial for workers employed at service providers compared to manufacturers. In Subsection 4.3, we provide evidence suggesting that the differences between service providers and manufacturers are driven by different responses to office and communication equipment compared to production equipment.

Overall, our key finding is that the employment stability has, on average, improved in response to technology adoption. Workers do not experience prolonged unemployment after firms' adoption of digital technologies compared to workers of non-adopting firms. However, the higher employment stability is more pronounced and significant for 3.0-adoption than for 4.0-adoption. On the one hand, this could indicate that the most recent 4.0-technologies generate less labor demand compared to 3.0-technologies. On the other hand, it could reflect that 4.0-adopters are currently still in a phase where they are investing in more recent technologies, such that productivity gains and business expansions have not yet been fully realized. Moreover, the differentiation between workers of service providers versus manufacturers suggests that technology adoption is especially beneficial for workers employed at service providers. This could be related to other findings according to which labor demand in service industries profits relatively more (suffers relatively less) from technology adoption compared to manufacturing industries (see, e.g., Acemoglu and Restrepo, 2020; Dauth et al., 2021b).

4.2.2 Wage Growth

Table 5 shows individuals' wage adjustments in reaction to recent technology adoption. We differentiate the analysis for individuals employed at the original employer after five years (hereafter referred to as stayers) and individuals that separate from their original employer and switch to employment at a different employer (hereafter referred to as switchers). For both groups, we estimate an OLS model based on the individual cross-sectional data (Columns 1 and 4), a version with individual-level controls (Columns 2 and 5), and a model with both individual- and firm-level controls (Columns 3 and 6). All results are shown for all workers (Panel A) and separately for workers initially employed at service providers (Panel B) and manufacturers (Panel C). Since we look at differences in log daily wages between 2016 and 2011, we multiply all estimates by

Table 5: Adjustments in Workers' Wage Growth to Firms' Technology Investments

Dependent variable: (five year) 100 ×Δ log daily wage of workers..	..employed at original employer (stayers)			..employed at different employer (switchers)		
	(1)	(2)	(3)	(4)	(5)	(6)
A. All Firms (N=113,704)						
3.0-adopters	1.55	1.72	2.28	-11.84*	-8.37*	-8.05**
	(0.99)	(1.11)	(1.65)	(-1.74)	(-1.78)	(-1.97)
4.0-adopters	2.74**	2.66**	2.67*	-13.26*	-10.56**	-11.93**
	(2.00)	(2.02)	(1.72)	(-1.78)	(-1.99)	(-2.47)
	N=88,363			N=25,341		
B. Service Providers (N=54,920)						
3.0-adopters	2.37	2.32	3.65**	-13.74*	-9.13*	-9.68**
	(1.21)	(1.16)	(2.27)	(-1.76)	(-1.77)	(-2.13)
4.0-adopters	3.91**	3.33*	3.82*	-15.11*	-11.50*	-12.80**
	(2.33)	(1.88)	(1.90)	(-1.76)	(-1.95)	(-2.41)
	N=39,316			N=15,604		
C. Manufacturers (N=58,784)						
3.0-adopters	-0.87	-0.01	0.40	-1.74	-1.52	1.43
	(-0.37)	(-0.00)	(0.24)	(-0.60)	(-0.61)	(0.57)
4.0-adopters	-0.54	0.27	1.50	-7.01**	-6.84***	-3.18
	(-0.23)	(0.15)	(0.90)	(-2.02)	(-2.60)	(-1.17)
	N=49,047			N=9,737		
Ind. cov.		✓	✓		✓	✓
Firm cov.			✓			✓

Notes: All models are estimated with OLS based on the cross-sectional data and weighted with firm stratification weights. Subsection 4.1 describes the individual- and firm-level covariates. The coefficients are multiplied by 100 to represent percentage point differences between 3.0- or 4.0-adopters compared to non-adopters. Robust standard errors are clustered at the firm level. t-statistics in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

100, such that the estimates represent percentage point differences between 3.0- or 4.0-adopters compared to non-adopters (hereafter abbreviated with pp).

We find evidence for increased wage growth in response to technology adoption among individuals remaining employed at their original employer (Columns 1-3). The coefficients for both 3.0-adoption and 4.0-adoption are positive (+2.3pp and +2.7pp) when including individual- and firm-level controls (Column 3), although only the coefficient for 4.0-adoption is significant (at the 10% significance level).

Regarding switchers, we find evidence for slower wage growth in response to technology adoption (Columns 4-6). In particular, over the five years, investments into 3.0-technologies statistically significantly reduced the wage growth of switchers by 8.1pp (Column 6 with individual- and firm-level controls) relative to non-adopters. The reduction is even more substantial for switchers from 4.0-adopters (-11.9pp). It is important to note that the wage growth of individuals switching away from non-adopters is more pronounced than the wage growth of switchers from 3.0- or 4.0-adopters, whereas the absolute wage growth is positive irrespective of the adoption status.

Similar to the results for workers' employment stability, we find that the wage adjustments are driven by service providers. Accordingly, workers in 3.0-adopting service firms experience a significant 3.7pp higher wage growth compared to workers in non-adopting firms (Panel B Column 3). For 4.0-adoption, the difference amounts to 3.8pp, although significant only at the 10% significance level. For individuals employed at manufacturing firms, the correlations between wage growth and technology adoption are much smaller and insignificant. Also, the declines in wage growth of worker switching away from service providers (Panel B Columns 4-6) are similar to Panel A (-9.7pp for 3.0-adoption and -12.8pp for 4.0-adoption), whereas insignificant for workers switching away from manufacturing firms (Panel C). We demonstrate in Subsection 4.3 that the different wage adjustments between workers in adopting service firms and manufacturers stem from heterogeneous responses between the adoption of office and communication equipment and production equipment.

Overall, our evidence suggests that workers remaining employed at their original employer experience improved wage growth in response to 4.0-technologies, while corresponding evidence for 3.0-technologies is only weak. This could indicate that after a period of relatively slow productivity growth (productivity paradox, see Gordon, 2016) as a result of a transition to an era of new technologies (Brynjolfsson et al., 2019), firms' investments are slowly beginning to pay off. The enhanced wage growth is most pronounced for workers at service providers. Similarly, Humlum (2019) shows that tech workers (such as computer programmers and engineers) and service workers experience the highest real wage increase in response to robot adoption, while production workers in manufacturing suffer from wage declines.[14] Furthermore, we find that the enhanced wage growth of stayers contrasts the wage response of switchers to technology adoption, who experience reduced wage growth. This finding is similar to other studies suggesting that

[14]Decomposing the net wage effect, Humlum (2019) shows that the adoption of industrial robots leads to a lowered labor demand for production workers, which depresses production workers' wages. At the same time, there is an additional positive wage effect for these workers due to a shift in labor supply away from production towards tech jobs, though not large enough to compensate for the negative labor demand effect.

automation leads to wage losses for workers who separate from the original employer and thereby creating a gap to those workers who remain at the adopting firms (see, e.g., Dauth et al., 2021b; Bessen et al., 2019).

4.3 Robustness

Technology Adoption Measure. We test how sensible our results are to our definition of technology adoption by constructing two alternative technology adoption measures:

First, we test whether our results are robust to using a different time-constant weight δ_j to aggregate the survey technology shares $k_{jst}^{O\&C}$ and k_{jst}^{Prod} into one aggregate measure, as defined in Equation 1. We use the firm-specific share of blue-collar workers δ_j based on the German classification of occupations *KldB 2010* instead of the International Standard Classification of Occupations *ISCO 2008*. Panel A of Appendix Table 17 displays the employment stability results with the alternative weighting parameter and confirms the main employment stability results of Panel A of Table 4. The coefficient for days employed at the original employer for 3.0-adoption in Column (3) increases from +63 to +73 and remains statistically significant. Similarly, the main wage results of Panel A of Table 5 are confirmed when applying the alternative blue-collar worker share in Appendix Table 18. The positive wage response of stayers in 4.0-adopting firms in Column (3) slightly declines from +2.7 to +2.5, while the coefficient for 3.0-adoption remains stable at about +2.2. Both comparisons suggest that our main results are not sensitive to the specific weighting parameter δ_j applied in the technology adoption measure.

Second, we conduct an alternative test and drop the weighted aggregation of office and communication equipment and production equipment in Equation 1. In particular, we assume that service providers only use office and communication equipment $k_{jst}^{O\&C}$, whereas manufacturers only use production equipment k_{jst}^{Prod} and re-estimate Panels B and C of Tables 4 and 5. This way, we also reveal potential heterogeneity between manufacturing-related technologies (e.g., industrial robots) and service-related technologies (e.g., personal computers and AI). Overall, the results in Appendix Tables 17 and 18 largely confirm our findings for employment stability and wage growth across workers from service and manufacturing firms.[15] The notably enhanced positive employment and wage adjustments to technology adoption of service providers further

[15] A smaller deviation refers to a slightly significant coefficient for 3.0-adoption among manufacturers in Column (3) of Panel B2 in Table 17. Despite remaining half the size of the corresponding coefficient for service providers, this is the only coefficient that rises in magnitude when comparing Panel B2 between Table 4 and Table 17 as well as Table 5 and Table 18.

suggest that the more favorable labor market performance relates considerably to technology adoption among office and communication equipment. In contrast, the lack of beneficial adjustments for workers from manufacturers may indicate a potential absence of beneficial responses arising from technological upgrading among production equipment.

Employment Probabilities. Since counting the number of days employed or unemployed coincides with a censoring at the top (i.e., employment throughout the entire time period censors the accumulated days employed at the five-fold of 365), we re-estimate our employment results with employment probabilities after five years based on logit models. We estimate Equation 2 with following probabilities as outcomes: (1) to remain employed at the original employer, (2) to switch to a different employer, or (3) to become unemployed. Table 6 shows the corresponding average marginal effects.

Table 6: Adjustments in Workers' Employment Stability to Firms' Technology Investments - Employment Probability (Logit Models, Average Marginal Effects)

Dependent variable: probability that (after five years) a worker is..									
	..employed at original employer			..employed at different employer			..unemployed		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
3.0-adopters	9.38***	4.92**	5.40**	-6.25**	-1.96	-2.10	-2.62**	-1.77**	-1.77**
	(2.85)	(2.26)	(2.43)	(-2.12)	(-1.02)	(-1.11)	(-2.43)	(-2.10)	(-2.25)
4.0-adopters	4.60	0.87	1.87	-2.10	0.84	0.29	-2.11*	-1.25	-1.43*
	(1.27)	(0.35)	(0.73)	(-0.62)	(0.36)	(0.12)	(-1.86)	(-1.42)	(-1.65)
Ind. cov.		✓	✓		✓	✓		✓	✓
Firm cov.			✓			✓			✓

Notes: N=172,714. The table shows average marginal effects based on logit models applied to the cross-sectional data and weighted with firm stratification weights. Subsection 4.1 describes the individual- and firm-level covariates. The coefficients are multiplied by 100 to represent percentage point differences between 3.0- or 4.0-adopters compared to non-adopters. Robust standard errors are clustered at the firm level. t-statistics in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

The result from the specification with the complete set of controls (Column 3) suggests a significant 5.3pp higher probability to remain employed at the original employer in response to 3.0-technology investments, conditional on being employed at the firm in 2011. We do not find statistically significant adjustments for 4.0-technology adoption. As before, we also find no adjustments for the probability of being employed at a different employer five years later (Column 6). However, we find a statistically significant reduction in the probability of being unemployed in response to 3.0-adoption (Column 9). Overall, these estimates broadly confirm our main finding that 3.0-technologies increase the employment stability of workers in the adopting firm, while this is not the case for 4.0-technologies.

Cumulative Earnings. We now investigate whether the wage adjustments translate into earnings gains. We measure the cumulative earnings over the five years from 2011 to 2016 by summing up the number of days employed multiplied with the corresponding daily wage. Table 7 shows the results.

Table 7: Adjustments in Workers' Earnings to Firms' Technology Investments

Dependent variable: (five year) cumulative earnings of workers..						
	..employed at original employer (stayers)			..employed at different employer (switchers)		
	(1)	(2)	(3)	(4)	(5)	(6)
3.0-adopters	20.47***	15.87***	8.80**	16.04***	9.52***	3.60
	(3.55)	(3.43)	(2.23)	(3.84)	(3.25)	(1.22)
4.0-adopters	22.78***	17.34***	5.46	17.15**	10.46**	2.63
	(3.78)	(3.58)	(1.28)	(2.51)	(2.24)	(0.67)
Ind. cov.		✓	✓		✓	✓
Firm cov.			✓			✓
No. of individuals		88,363			25,341	

Notes: All models are estimated with OLS based on the cross-sectional data and weighted with firm stratification weights. Subsection 4.1 describes the individual- and firm-level covariates. The coefficients are multiplied by 100 to represent differences in percent between 3.0- or 4.0-adopters compared to non-adopters. Robust standard errors are clustered at the firm level. t-statistics in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

For workers remaining employed at their original employer (Columns 1-3), we find that in response to 3.0-adoption, the statistically significantly higher number of days employed at the initial firm and the insignificant higher wage growth translate into 8.8% higher labor earnings. For 4.0-adoption, the insignificant higher employment stability combined with the statistically significant higher wage growths result in a positive correlation between 4.0-technology adoption and cumulative earnings (Column 1). However, after adding individual and firm controls, the coefficient is smaller in magnitude (+5.5%) and not significant anymore. In levels, 3.0-technology adoption yields on average additional $14,521$ euros and 4.0-adoption additional $11,902$ euros relative to the average cumulative earnings of workers employed at non-adopters.

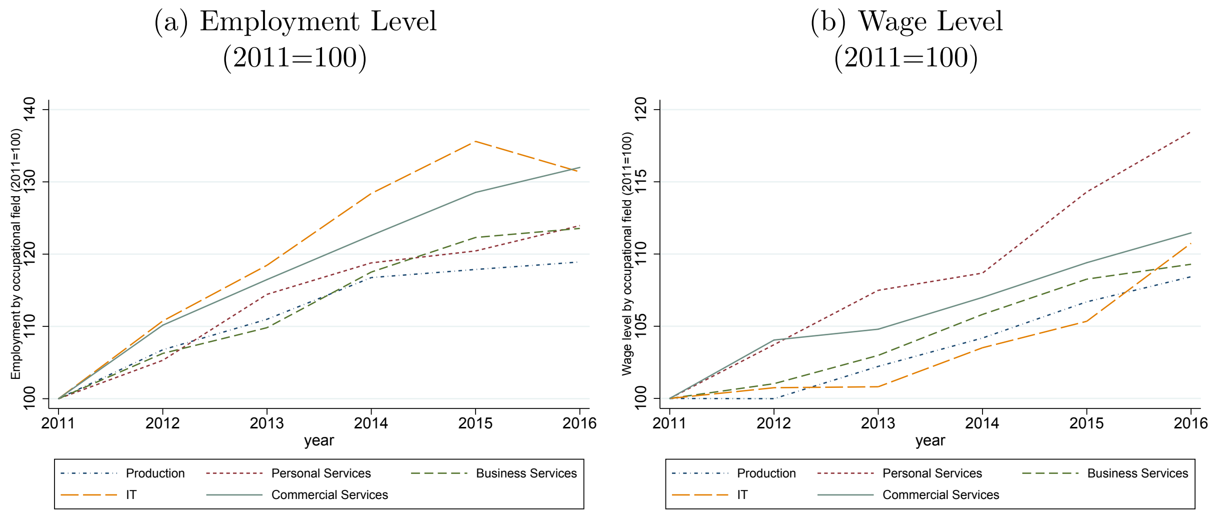
Furthermore, Table 7 documents that the slower wage growth of individuals who separate from adopting firms to work at different employers compared to switchers from non-adopters does not translate into cumulative earnings losses. In contrast, the coefficients for 3.0- and 4.0-adoption on cumulative earnings are positive and significant (+16.0% and +17.2% respectively in Column 4). This is true even after controlling for individual- and firm-level covariates, despite the coefficients losing significance and decreasing in magnitude (+3.6% and +2.6% in Column 6). This suggests that the higher number of days in employment and the higher average absolute wages in adopting firms save switching individuals from experiencing cumulative earnings losses.

5 Heterogeneous Adjustments Across Worker Groups

In this Section, we investigate the heterogeneity of our estimated worker adjustments to firms' investments across different worker groups. Past automation waves have shown to complement non-routine workers – both low- and high-income – at the expense of middle-income routine workers, also referred to as job polarization (Autor et al., 2003). Suggestive evidence indicates that more recent technologies such as AI might replace (and complement) very different workforce groups than earlier waves of automation (Brynjolfsson et al., 2018; Webb, 2020). Accordingly, tasks that are "suitability for machine learning" might increasingly be replaced, thus transforming many jobs in the economy through a reorganization of tasks. Consequently, one outcome might be that IT-related tasks will gain importance within all occupations and industries. In fact, if we look at the employment trends of different occupations across all sectors in Germany, we find the strongest employment growth among IT-related occupations (see Panel a of Figure 1). At the same time, wage growth for IT jobs was the weakest until 2015, before it picked up in the last year of our observation period.

To shed light of the potential role of firm technology adoption on these patterns, we consider adjustments in accumulated days employed and workers' wage growth across the following dimensions: occupational fields (Subsection 5.1), job requirements (Subsection 5.2), tasks (Subsection 5.3) and education (Subsection 5.4), following otherwise the same approach outlined in Subsection 4.1. For completeness, Appendix Section A.4 gives the corresponding coefficients and t-statistics displayed in the subsequent figures together with results for employment days at different employers, days spent in unemployment, and the wage growth for switchers.

Figure 1: Occupational Employment and Wage Trends (2011-2016)



Notes: Panel (a) shows the employment and Panel (b) the wage trends by occupational fields as defined in Appendix Subsection A.1.3. Figures are based on the linked employer-employee data set and weighted with firm stratification weights. Daily wages are measured in nominal terms and refer to full-time workers. Appendix Figure 6 displays the employment and wage trends based on the entire workforce in Germany which confirm the trends based on our sample.

5.1 Occupational Fields

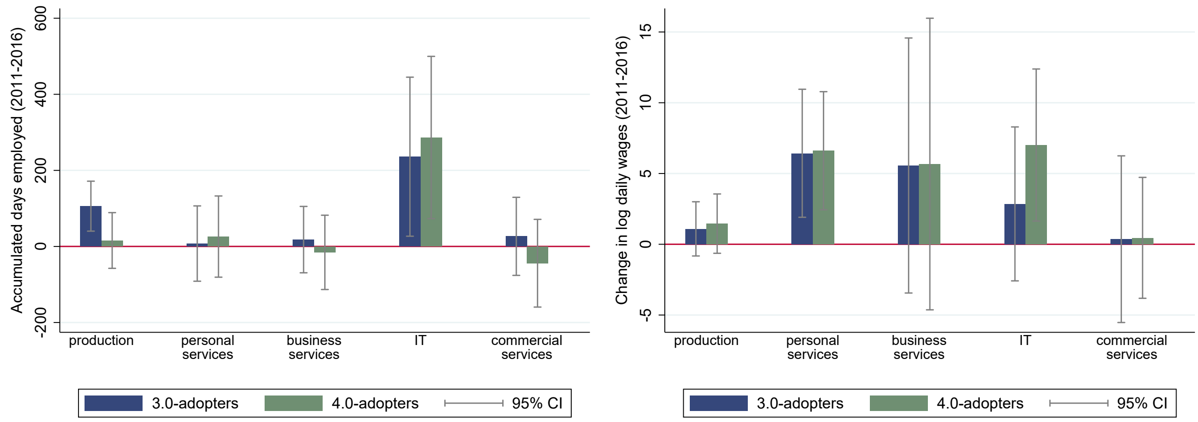
As a first dimension, we investigate worker adjustments by five occupational fields as explained in Appendix Subsection A.1.3. The results are shown in Figure 2. Panel (a) displays the adjustments in the accumulated days workers are employed at 3.0- and 4.0-adopting employers relative to non-adopters. Panel (b) shows the wage growth in response to 3.0- and 4.0-adoption for stayers.

Regarding employment, we find positive and significant responses in the accumulated days employed at the original employer in reaction to technology adoption for workers employed in IT occupations (Panel a of Figure 2). In particular, 4.0-technologies increase the employment stability of IT workers by 286 days, 3.0-technologies by 236 days. Furthermore, 3.0-technology adoption is associated with a positive response for production jobs (+106 days). However, when focusing on days employed at other employers, we do not find any significant adjustments by occupational fields (see Appendix Table 20). Comparing the positive employment response of IT and production workers to the overall employment stability results in Table 4, we have to keep the employment share of workers across occupational fields in mind. Only 3% of the workers conduct IT-related jobs, while almost one in three workers performs a production occupation. Thus, the positive employment stability response of IT occupations to 4.0-adoption is not reflected in the

Figure 2: Worker Adjustments to Firms' Technology Investments by Occupational Fields

(a) Accumulated number of days employed at original employer

(b) Δ Log daily wage of stayers



Notes: All models are estimated with OLS and weighted with firm stratification weights. Appendix Table 20 gives the corresponding coefficients and t-statistics. Subsection 4.1 describes the individual- and firm-level covariates. Estimates in Panel (a) are in days and in (b) in pp. Robust standard errors are clustered at the firm level. Whiskers represent 95% confidence intervals.

overall employment adjustment, while workers in production jobs drive the positive employment response to 3.0-adoption.

Regarding wages of stayers (Panel b of Figure 2), we find positive responses to wage growth of IT-workers in reaction to both 3.0-adoption and 4.0-adoption, although the coefficient is only statistically significant for 4.0-adoption (+7pp). This finding is in line with previous literature demonstrating that IT-related occupations such as computer programmers experience substantial wage increases in response to robot adoption, irrespective of the sector (see, e.g., Humlum, 2019). We do not find any significant wage adjustments for production occupations. Moreover, we find that wage growth of personal service jobs significantly increased in response to both 3.0-technology adoption (+6.4pp) and 4.0-technology adoption (+6.6pp). The fact that we only find increased wage growth and no employment responses for personal service occupations might speak for labor supply constraints in this occupational field (such as medical occupations and occupations in teaching). In contrast, switchers experience a slowdown in wage growth following technology adoption. Workers in personal service occupations and IT-jobs exposed to 3.0-adoption and production workers exposed to 4.0-adoption experience a lower wage growth compared to switchers of non-adopting firms (see Appendix Table 20).

The results point towards a rising prevalence of IT occupations. This might imply corresponding shifts in job requirements demanded in the increasingly digitized German labor market.

In fact, responses to a separate representative survey among individuals working in 2011 in one of the 2,032 surveyed firms illustrate that IT occupations require substantially higher programming skills.[16] Although our administrative data does not contain direct measures for programming skills, we can measure more general occupational requirements in the form of different levels of task complexity within occupations, as demonstrated in the following.

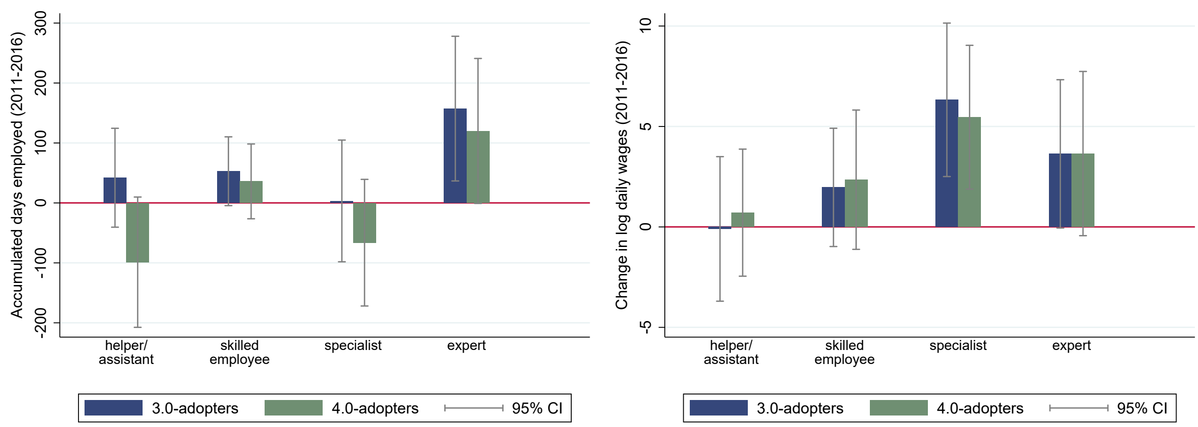
5.2 Job Requirements

The shifts between occupational fields towards IT occupations are also reflected in shifts towards higher task complexity within occupations. To demonstrate this, Figure 3 shows the results for employment days and changes in wage growth separately for workers across four job requirement categories that differentiate the degree of complexity within occupations: helpers/assistants, skilled employees, specialists, and experts, as defined in Subsection 2.2.

Figure 3: Heterogeneous Worker Adjustments by Job Requirements

(a) Accumulated number of days employed at original employer

(b) Δ Log daily wage of stayers



Notes: All models are estimated with OLS and weighted with firm stratification weights. Appendix Table 21 gives the corresponding coefficients and t-statistics. Subsection 4.1 describes the individual- and firm-level covariates. Estimates in Panel (a) are in days and in (b) in pp. Robust standard errors are clustered at the firm level. Whiskers represent 95% confidence intervals.

Regarding employment at the original employer, Panel (a) of Figure 3 displays a statistically significant increase in the number of days employed at the original employer for experts in response to 3.0-technology (+157 days) and 4.0-technology adoption (+120 days). The response of skilled employees to 3.0-technology adoption is also positive but less pronounced (+52 days).

[16] Appendix Table 14 displays that 41.8% of all workers in IT occupations write their own program scripts. In contrast, only 5.7% of workers in production occupations write programs, and program writing skills are merely unnecessary in personal service occupations, business service occupations, and commercial service occupations.

Furthermore, the results suggest a declining relevance of helpers (−99 days) and specialists (−66 days, however, not significant) at 4.0-adopting firms. The higher employment stability for experts at the original employer is also reflected in reduced employment days at other employers (Appendix Table 21).

Panel (b) of Figure 3 shows the wage responses for stayers. The results indicate increased wage growth for both specialists and experts in response to technology adoption. For specialists, the increase in reaction to the adoption of 3.0-technologies (+6.3pp) is slightly larger than for 4.0-technologies (+5.5pp). We also find positive adjustments for experts, although less pronounced and less precisely estimated (+3.6pp for both 3.0- and 4.0-technology adoption). Regarding switchers, we find statistically significant negative wage adjustments for skilled employees, which are stronger for 4.0-adoption (−15.3pp) compared to 3.0-adoption (−9.7pp), see Appendix Table 21.

Altogether, this suggests a shift towards more complex job requirements in response to technology adoption. Especially experts conducting highly complex work tasks on their jobs profit from higher employment stability and wage growth following 3.0- and 4.0-technology adoption. Also, workers who perform complex specialist tasks experience significantly higher wage growth when remaining employed at the adopting employer.

5.3 Tasks

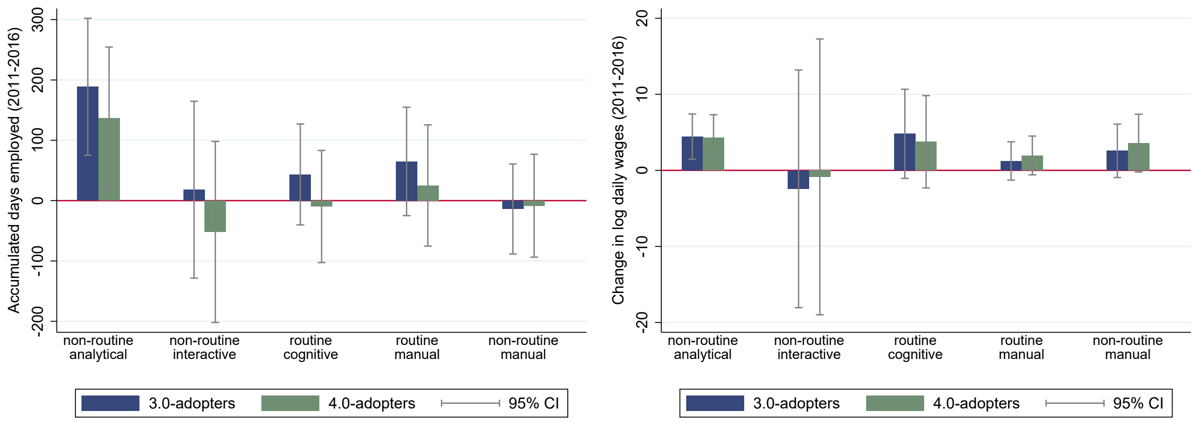
Besides the degree of task complexity, we also differentiate jobs by the degree of routine intensity and manual versus cognitive work according to Autor et al. (2003). Specifically, we distinguish between five main task categories as defined in Subsection 2.2. The results in Figure 4 suggest a statistically significantly higher employment stability for non-routine analytic workers in response to 3.0- and 4.0-adoption (Panel a). Non-routine analytic workers are on average 189 days longer employed at 3.0-adopting and 136 days longer employed at 4.0-adopting firms than similar workers at non-adopting firms. We do not find any significant adjustments for the remaining task groups. The pattern for days employed at different employers broadly mirrors these results (statistically significant −102 days following 3.0-adoption and −78 days following 4.0-adoption, although not significant, see Appendix Table 22).

The wage adjustments coincide broadly with the employment adjustments, i.e., we find positive and statistically significant wage responses for non-routine analytic workers staying employed at the investing firm (+4.4pp for 3.0- and +4.3pp for 4.0-technology adoption). Wage

Figure 4: Heterogeneous Worker Adjustments by Tasks

(a) Accumulated number of days employed at original employer

(b) Δ Log daily wage of stayers



Notes: All models are estimated with OLS and weighted with firm stratification weights. Appendix Table 22 gives the corresponding coefficients and t-statistics. Subsection 4.1 describes the individual- and firm-level covariates. Estimates in Panel (a) are in days and in (b) in pp. Robust standard errors are clustered at the firm level. Whiskers represent 95% confidence intervals.

changes for routine cognitive, routine manual and non-routine manual workers are positive, but mostly insignificant. For switchers, we find negative wage responses for almost all task groups, which are most pronounced for routine cognitive workers and non-routine analytic workers (see Appendix Table 22).

Overall, the differentiation between the five main task categories indicates a shift towards non-routine analytic work content, which fits the beneficial labor market adjustments of workers conducting highly complex jobs. The pattern is in line with the previous literature as it depicts the relative increase in non-routine analytic tasks, which complement automation technology. The fact that we do not find similar positive responses for non-routine interactive tasks presumably originates from our focus on workers' main tasks.[17]

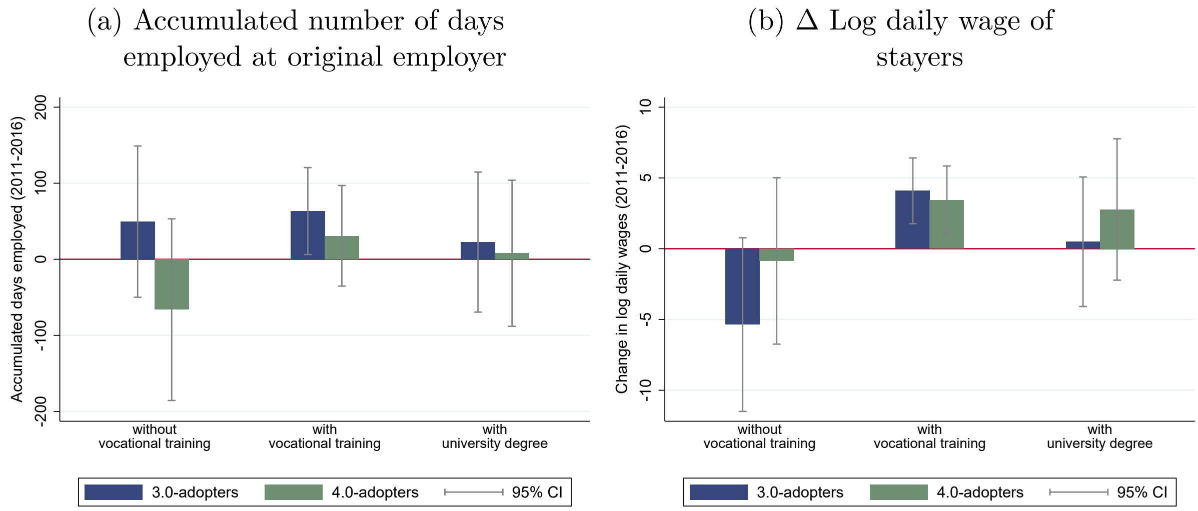
5.4 Education

Studies claim that new technologies such as AI may increasingly take over jobs in the domains of white-collar workers, including academic workers (Brynjolfsson et al., 2018; Webb, 2020). To shed some empirical light on these predictions, we look at workers' responses to technology adoption separately by three education categories: workers with (1) no vocational training

[17]Interactive tasks rarely constitute the dominating task category within an occupation and often account for an essential part of occupations with predominantly non-routine analytic work content.

degree, (2) vocational training degree, and (3) university or technical college degree. Figure 5 shows the corresponding employment and wage adjustments following 3.0- and 4.0-investments for workers across these three education groups. Appendix Table 23 displays the estimates of the corresponding regression analyses.

Figure 5: Heterogeneous Worker Adjustments by Education



Notes: All models are estimated with OLS and weighted with firm stratification weights. Appendix Table 23 gives the corresponding coefficients and t-statistics. Subsection 4.1 describes the individual- and firm-level covariates. Estimates in Panel (a) are in days and in (b) in pp. Robust standard errors are clustered at the firm level. Whiskers represent 95% confidence intervals.

Panel (a) of Figure 5 shows that the number of employment days at the original employer statistically significantly increase for workers with vocational training following 3.0-investments (+64 days). The coefficients for the other worker groups are insignificant. For 4.0-technology adoption, we find fewer days employed at the original employer for workers without vocational training and more days employed for workers with vocational training or university degrees, however none of the estimates is significant. We also do not find any significant adjustments related to the days employed at other employers (Panel B of Appendix Table 23). This might suggest that shifts towards more complex job requirements do not necessarily coincide with more academic skills. In fact, we even find a positive response in unemployment days (+43 days) for academics in response to 4.0-adoption.

Regarding wage growth of stayers (Panel b of Figure 5), we find a statistically significant wage growth among workers with vocational training in reaction to technology investments, both for 3.0-technologies (+4.1pp) and 4.0-technologies (+3.4pp). Furthermore, workers without vocational training experience a 5.4pp lower wage growth when staying at the original 3.0-adopting firm compared to workers staying at non-adopting firms. Individuals that separate from an adopting employer and switch to employment at a different employer experience generally a lower wage growth compared to switchers from non-adopters (Panel E of Appendix Table 23). The negative wage adjustments are most pronounced for switchers with vocational training, both following 3.0-adoption (−8.1pp) and 4.0-adoption (−13pp).

In summary, our results suggest that workers with vocational training benefit most from technological upgrading in terms of employment stability and wage growth. At first glance, the findings might surprise: We find beneficial labor market performance for IT jobs, experts, and workers conducting non-routine analytic tasks, such that one might also expect positive labor market adjustments for university graduates. However, we find that the benefiting expert jobs are conducted by workers with vocational training rather than those with a university degree (e.g., occupations in business organization and strategy or technical production planning controllers). One explanation might be that Germany's traditionally strong vocational training system (76% of all workers in the sample completed vocational education) already provides sufficient specialized skills such that university degrees are not necessarily required. In fact, one in three young individuals entering fully-qualifying vocational education and training programs hold a university entrance qualification and can thus be attributed to the highly skilled segment (Haasler, 2020). Another likely explanation is that IT-expert jobs and jobs with non-routine analytic tasks require higher education, but workers are currently hard to find or retain.

6 New Hires

So far, our analysis has focused on workers that were employed in one of the surveyed firms on June 30, 2011. To provide a complete picture of the worker adjustments in response to technology adoption, we also look at adjustments at the hiring margin. For instance, it might be that adopting 4.0-technologies leads firms to hire different workers such that shifts in the composition of workers in response to technological upgrading take place through hiring rather than through adjustments among incumbent workers.

We study how worker characteristics influence the hiring probability between adopting and non-adopting firms between 2012 and 2016 in Table 8. Columns (1)-(4) show the corresponding estimates of simple logit regressions where we regress the probability that a worker enters a 3.0-adopting firm compared to non-adopting firms successively on selected individual character-

Table 8: Hiring Probability of Individuals at Adopting vs. Non-Adopting Firms
(Logit Models, Average Marginal Effects)

Dependent variable: probability to start a new job at....								
	...3.0-adopters relative to non-adopters				...4.0-adopters relative to non-adopters			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age	0.05	0.05	0.05	0.05	-0.20*	-0.20*	-0.20*	-0.20*
	(0.67)	(0.65)	(0.67)	(0.67)	(-1.80)	(-1.85)	(-1.81)	(-1.85)
Occupational fields (rel. to production):								
Personal services	0.64	0.58	0.61	0.64	-6.97	-8.33	-7.88	-8.49
	(0.09)	(0.08)	(0.08)	(0.09)	(-0.93)	(-1.13)	(-1.08)	(-1.16)
Business services	15.81***	15.84***	15.78***	15.94***	19.39***	19.45***	18.70***	19.14***
	(2.84)	(2.84)	(2.86)	(2.88)	(3.64)	(3.62)	(3.47)	(3.55)
IT	7.79	7.10	7.76	7.10	14.23	11.84	12.42	11.46
	(0.68)	(0.63)	(0.67)	(0.63)	(1.30)	(1.14)	(1.18)	(1.11)
Commercial services	1.48	1.72	1.49	1.72	-15.62**	-14.02*	-14.43*	-13.79*
	(0.20)	(0.23)	(0.20)	(0.23)	(-2.08)	(-1.87)	(-1.93)	(-1.85)
Expert job requirements		3.51		4.07		15.37**		13.21**
		(0.84)		(0.90)		(2.28)		(2.11)
University degree			0.36	-1.03			9.05*	3.59
			(0.11)	(-0.29)			(1.65)	(0.78)
Firm cov.	✓	✓	✓	✓	✓	✓	✓	✓
No. of individuals	70,372				58,160			

Notes: The table shows average marginal effects based on logit models applied to the cross-sectional data and weighted with firm stratification weights. Subsection 4.1 describes the firm-level covariates. The coefficients are multiplied by 100 to represent percentage point differences between 3.0- or 4.0-adopters compared to non-adopters. Robust standard errors are clustered at the firm level. t-statistics in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

istics, including age, occupational fields, job requirements and education and additionally controlling for firm characteristics including firm size, sector and federal state. In Columns (5)-(8) of Table 8 we further differentiate the hiring probability between entering 4.0- versus non-adopters. All estimates are clustered at the firm level.

The results show that the probability of entering 3.0-adopters, relative to entering non-adopters, is statistically significantly higher for workers who conduct business services jobs (Column 1), potentially speaking for business expansions. IT workers are also more likely to enter 3.0-adopters (between +7.1 and +7.8pp), albeit the coefficient is insignificant. To account for higher task complexity within occupations, we separately add a dummy for expert job requirements (Column 2) and a university degree dummy (Column 3) before including both covariates simultaneously (Column 4). Despite the lack of significance, the results tentatively suggest that expert workers have a higher probability of entering 3.0-technology adopters (+3.5pp) than entering non-adopting firms, even when controlling simultaneously for having a university degree (+4.1pp). The coefficient for workers with a university degree is small and even turns negative when controlling for expert job requirements, although insignificant. These results suggest that business service jobs profit from 3.0-adoption at the hiring margin, whereas evidence for beneficial adjustments among IT-experts is less strong as found for incumbent workers in Section 5.

Focusing on the difference between 4.0-adopters and non-adopters (Columns 5-8), we see that hires of 4.0-adopters are younger than hires of non-adopters. Moreover, compared to non-adopters, workers entering 4.0-adopters are more often employed in business service jobs (+19.4pp) and IT jobs (+14.2pp), although the latter is not statistically significant. Individuals conducting commercial service jobs are significantly less likely (−15.6pp) to enter 4.0-adopters compared to non-adopters. Moving to Column (6), we find that individuals who conduct highly complex job tasks have a significant higher probability of entering 4.0-adopting firms than non-adopting firms (+15.4pp), even after controlling for having a university degree (+13.2pp in Column 8). Individuals with a university degree have a significantly higher probability of entering 4.0-adopters than non-adopters (+9.1pp in Column 7), albeit the positive coefficient decreases and is not significant anymore when controlling simultaneously for expert job requirements (+3.6pp in Column 8). This suggests that hiring experts is more important for 4.0-adopters than hiring academics, compared to non-adopters.

Altogether, the analysis at the hiring margin points towards adjustments similar to the proceeding analysis for incumbent workers. Accordingly, investments in new technologies shift labor demand towards IT occupations with highly complex work tasks (such as IT security consultants, cloud engineers, or AI specialists), although these shifts are more pronounced among 4.0-adopters than for 3.0-adopters at the hiring margin. Moreover, younger workers profit from better hiring probabilities when entering 4.0-adopters. This result is in line with Aubert et al. (2006), who find a decrease in hiring for older workers in the case of computer use (explained with skills obsolescence or adaptability problems). Finally, the analysis points towards general business expansions as a result of technology adoption.

7 Conclusion

This study examines how workers adjust to new technologies based on new linked employer-employee data including survey information on firms' technology adoption. The data allows to identify firms' investments into cutting-edge 4.0-technologies including AI, AR, or 3D printing as distinguished from 3.0-technologies such as personal computers, CNC machines, or industrial robots. In particular, we compare individual-level outcomes between workers from adopter and non-adopter firms.

Our results do not support fears that modern technologies largely substitute for human labor. In contrast, our evidence suggests increased employment stability, wage growth and cumulative earnings in response to digital technology adoption. However, the beneficial labor market adjustments split differently across digital technologies: older digital 3.0-technologies relate to a significant increase in workers' employment stability and translate into higher cumulative labor earnings. In comparison, more recent digital and connected 4.0-technologies are associated predominantly with significantly pronounced wage growth without corresponding pronounced adjustments in employment days and earnings. On the one hand, this could indicate that cutting-edge 4.0-technologies are less "brilliant" than expected (similar to "so-so" technologies described by Acemoglu and Restrepo, 2019). On the other hand, it could reflect that 4.0-technology adopter firms are currently still in an investment and transition phase, such that their productivity gains and business expansions from these technologies have not yet been fully generated and realized (Brynjolfsson et al., 2019).

We further find that workers at service providers profit more than those at manufacturers from firms' technology adoption. This finding relates to other studies that have already documented less favorable outcomes in response to technology adoption in manufacturing relative to service industries, albeit at different levels of aggregation (see, e.g., Acemoglu and Restrepo, 2020; Dauth et al., 2021b). As one possible explanation, we show that manufacturing-related technologies (e.g., industrial robots) tend to be more labor-saving compared to technologies predominantly used among service providers (e.g., personal computers and AI). One implication arising from this finding is that focusing on specific manufacturing-related technologies, as done by many studies on robot adoption, may be missing substantial parts of the beneficial adjustments from technology adoption more generally.

Finally, our analyses suggest that the benefits from new technologies largely depend on the job workers perform. In particular, our evidence suggests that workers in IT-related occupations benefit most in terms of increased employment stability, wage growth, and earnings. This trend is also associated with increased highly complex job requirements and a shift towards non-routine analytic work tasks. Surprisingly, this does not necessarily coincide with a higher demand for academic workers. In contrast, workers with vocational training (e.g., occupations in business organization and strategy or technical production planning controllers) benefit most from technological upgrading. This might reflect the strength of the German vocational training system or point towards supply shortages on the labor market such that firms currently do not find enough workers with academic skills.

As we demonstrate, cutting-edge technologies such as AI and AR still play a minor role across most German firms. However, our study shows that such technologies are spreading rapidly, with uneven adjustments across workers. Continued monitoring of the utilization and diffusion of modern technologies beyond our observation period is thus necessary to further improve the understanding of its labor market consequences.

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A Appendix

A.1 Data

A.1.1 Firm Survey

Non-Response. For the "IAB-ZEW Labor Market 4.0 Establishment Survey", the IAB randomly selected addresses from all firms registered at the German Federal Employment Agency in the year 2014 across the stratification cells sector (5 categories), firm size (4 categories) and location (East or West Germany). A resulting list of 12,366 randomly selected addresses was provided to an independent survey institute that conducted the survey. The observation target was to reach at least 50 interviews in each of the 40 cells. Table 9 shows that 2,841 firms were not contactable because the phone number was not available, wrongly matched or among the list of firms that were part of the pretest. From the remaining cases, 3,068 firms were generally contactable, but either the number was busy or the survey institute made an appointment with the target or contact person without the interview ever taking place (for instance, because the

Table 9: Utilization of the total sample

	n	In % of total sample	In % of corrected sample
Total sample of firm contacts	**12,366**	**100%**	
Sample of deleted or incorrect firm contacts	**2,841**	**23.00**	
Phone number unknown	1,315	10.6	
Final processing in pretest (adjusted)	99	0.8	
Not contacted	194	1.6	
Not a firm	68	0.5	
Wrong firm	125	1.0	
Wrong legal form	254	2.1	
Fax/no dial tone/no connection	250	2.0	
Black list	536	4.3	
Sample of firms that were were not called	**3,068**	**24.8**	
Appointment with target person	80	0.6	
Appointment with contact person	1,312	10.6	
Telephone number busy/dial tone	1,676	13.6	
Sample of firm contacts that were called	**6,457**	**52.2**	**100%**
Interview denied	**4,227**		**65.5**
Started interviews with target person	**2,230**		**34.5**
Completed interviews	2,032		31.50
Aborted interviews	179		2.8
Interrupted during interview	19		0.3

observation target in the stratification cell was already reached). This left us with 6,457 firm contacts that were called for an interview (hereafter referred to as corrected sample). From these, 4,227 firms denied the interview. From the final 2,230 firms that started the interview, 179 firms aborted and 19 interrupted the interview for reasons discussed in more detail below. Accordingly, 2,032 firms successfully completed the interviews and thus full-filling our observation target across the stratification cells.[18] This corresponds to a response rate of 31.5% if the corrected sample is taken as the basis for calculation.

To allow investigations on whether the interview denials or abortions lead to a selective sample of firms interviewed, the survey institute tried to gather additional information in these cases. In particular, whenever the interviewee declined or aborted on the interview, the survey institute followed up on the reasons. Table 10 gives an overview of the reasons provided by the contact persons that denied the interview, ranging from general no participation in surveys (15.7%) or telephone surveys (17.9%), no time (22.3%), or no interest in the topic (23.6%).

Table 10: Reasons for Denied and Aborted Interviews

	Cases	in % of all cases
Number of denied interviews	**4,227**	**100%**
Generally no participation in surveys	663	15.7
Generally no participation in telephone surveys	755	17.9
No time	941	22.3
No interest in the topic of the study	997	23.6
No access to the target person	546	12.9
Target person ill/absent for a longer period of time	20	0.5
Difficulties in understanding	33	0.8
Firm has been closed	34	0.8
Other	93	2.2
No answer	145	3.4
Number of aborted interviews	**179**	**100%**
No time	18	10.1
No interest in the topic of the study	8	4.5
Difficulties in understanding	3	1.7
Difficulties in answering the questions	31	17.3
Other	28	15.6
No answer	91	50.8

The latter answer is meaningful as it is informative about the presence of a potential non-response bias. If contact persons systematically deny the interview because the firm has not yet considered topics concerning automation and digitalization technologies, the firm survey

[18]Only the cells for firms with "50-200 employees" and "200 and more employees" in the East German ICT sector had to be merged in order to guarantee 50 interviews.

would suffer from a non-response bias. Therefore, given that the contact person has not yet ended the phone call, the survey institute asked a further question: "Is this because digitization and automation technologies do not play a role in your firm?". In the course of the ending conversation, it was only possible to ask 176 firms this further question (before they hung up or ended the call). From the 137 firms that answered the question, 81% answered "no" and 19% "yes". Altogether, this suggests that the non-response bias is not a cause of major concern. To further ensure that our sample of interviewed firms constitutes a representative sample of the German firm landscape, we compare several characteristics of the 2,032 firms that completed the interview to the entire population of firms we observe in register data (see next paragraph).

Representativity. To conduct the firm survey, firms within the stratification cells sector, firm size and location are randomly selected from the entire firm population in Germany in 2014. The entire German firm population amounts to more than three million firms and is based on the IAB Establishment History Panel (BHP -Version 2, 2019). To demonstrate that the 2,032 surveyed firms are a representative sample of the entire German firm population, Table 11 compares the characteristics of the 2,032 survey firms with those of the universe of firms in Germany in 2014.

Table 11 displays no differences concerning the stratification variables sector, firm size and location between the mean values of the entire German firm population and the mean values of the survey firms weighted with stratification weights. We also examine additional workforce characteristics beyond the stratification variables. Concerning the educational and occupational composition, the survey firms are very similar to the entire firm population. This is also reflected in almost identical mean and median daily wages that both groups of firms pay to their workers. There are only minor differences concerning the share of female workers, which is slightly higher among all German firms than among the survey firms. The largest difference is the higher share of skilled employees among the survey firms. However, the information on the job requirement, occupational and educational composition of the workforce may contain missing information for the entire firm population, whereas our sample preparation excludes employment spells with missing information in these variables as explained in Subsection 2.2. Given the similarity between the surveyed firms and the entire firm population shown in Table 11, we are confident that our sample of firms is representative for the firm landscape in Germany.

Table 11: Firm characteristics across the entire German firm population and the surveyed firms

	Entire firm population (1)	Survey firms (2)
Firm characteristics		
Share of firms by sector (in %):		
Non-knowledge intensive production	17.18	17.31
Knowledge intensive production	1.20	1.21
Non-knowledge intensive service	60.91	60.59
Knowledge intensive service	18.75	18.92
ICT	1.96	1.98
Share of firms by firm size (in %):		
0-9 emp.	80.49	79.06
10-49 emp.	15.82	17.21
50-199 emp.	3.00	3.09
200 and more emp.	0.68	0.65
East Germany (in %)	17.80	17.86
Workforce characteristics		
Female share (in %)	59.47	53.93
Mean daily wage (in euros)	80.44	81.04
Median daily wage (in euros)	78.41	79.28
Share of workers by education (in %):		
No vocational training	11.98	11.37
Vocational training	70.66	70.16
University degree	11.49	14.29
Share of workers by job requirement (in %):		
Helper/assistant	21.57	20.31
Skilled employee	54.37	62.67
Specialist	8.18	9.67
Expert	6.07	7.34
Share of workers by Blossfeld occupation aggregates (in %):*		
Agricultural occ.	3.81	4.55
Unskilled manual occ.	4.80	4.35
Unskilled service occ.	20.63	19.04
Unskilled commercial and administrative occ.	12.80	11.97
Skilled manual occ.	10.03	13.19
Skilled service occ.	8.33	6.98
Skilled commercial and administrative occ.	18.20	22.95
Technicians	2.43	4.46
Semi-professions	3.85	5.61
Engineers	1.26	2.34
Professions	0.98	0.80
Managers	3.07	3.77
No. of firms	3,022,995	2,032

Notes: Appendix Subsection A.1.2 explains the definition of the sector aggregates in detail. The BHP data, which provides the firm-level and workforce characteristics for the entire German firm population in Column (1), contains the occupational composition of firms across 12 occupation aggregates as described in Ganzer et al. (2021). Figures in Column (2) are weighted with firm stratification weights.

A.1.2 Sector Definition

In our classification of economic sectors, we follow the basic division along the primary (agriculture, fishing or mining), secondary (manufacturing or construction) and tertiary sectors (trade, banking, education or health services). Given that the primary sector does only employ a minor share of total employment (about 1.5%), we focus on the distinction between the secondary and tertiary sector. Instead, we further distinguish between knowledge-intensive and non-knowledge-intensive industries within the secondary and tertiary sectors and identified the ICT sector (information technology services or telecommunication services) separately. Firms of the primary sector are assigned to the non-knowledge intensive production sector. Table 12 lists the five sector aggregates and the corresponding 3-digit codes of the German Classification of Economic Activities 2008.

Table 12: Definition of Sectors

Sector Aggregate	German Classification of Economic Activities
Secondary Sectors:	
Non-knowledge intensive production	11-99, 101-182, 221-259, 310-439
Knowledge intensive production	191-212, 265-267, 271-309
Tertiary Sectors:	
Non-knowledge intensive service	451-464, 466-563, 681-683, 771-856, 871-889, 920-949, 952-990
Knowledge intensive service	581, 591-602, 639-663, 691-750, 861-869, 900-910
ICT Sector	261-264, 268, 465, 582, 611-631, 951

Notes: Column (1) displays the name of the five sector aggregates. Column (2) gives the corresponding time-consistent 3-digit codes of the German Classification of Economic Activities 2008 (WZ 2008), which can be translated directly into NACE Rev. 2 industry codes.

A.1.3 Occupational Field Definition

In this paper, we use the occupational field definition provided by the German Federal Employment Agency. The classification is based on the German classification of occupations *KldB 2010*, which is particularly suited for analyzing occupational labor markets as it grounds on a quantitative analysis of the similarity of occupational tasks profiles. For example, the classification yields a separate cluster for IT and natural science occupations due to the distinct task bundles within these occupations. Exemplary IT occupations include software developers (*KldB 2010*: 43414), database administrators (*KldB 2010*: 43353), and webmasters (*KldB 2010*: 43363).[19]

[19] The German Federal Employment Agency provides a conversion table to transfer the *KldB 2010* occupation codes into the International Standard Classification of Occupations *ISCO 2008*. The corresponding 4-digit *ISCO 2008* codes are for software developers – 2512, database administrators – 2521, and webmasters – 3514.

Table 13 provides a correspondence table between the five occupational fields and the corresponding 2-digit occupation codes of the *KldB 2010*. Table 14 provides additional statistics on the composition of workers within each field.

Table 13: Definition of Occupational Fields

Occupational field	2-digit Occupation Codes *KldB 2010*
Production	11 Occupations in agriculture, forestry, and farming
	12 Occupations in horticulture and floristry
	21 Occupations in production of raw materials, glass/ceramic-making and -processing
	22 Occupations in plastic-making and -processing, and wood-working and -processing
	23 Occupations in paper-making and -processing, printing, and in technical media design
	24 Occupations in metal-making and -working, and in metal construction
	25 Technical occupations in machine-building and automotive industry
	26 Occupations in mechatronics, energy electronics and electrical engineering
	27 Occupations in technical R&D, construction, and production planning and scheduling
	28 Occupations in textile- and leather-making and -processing
	31 Occupations in construction scheduling, architecture and surveying
	32 Occupations in building construction above and below ground
	33 Occupations in interior construction
	34 Occupations in building services engineering and technical building services
	93 Occupations in product design, artisan craftwork, fine arts and musical instruments making
Personal services	29 Occupations in food-production and -processing
	63 Occupations in tourism, hotels and restaurants
	81 Medical and health care occupations
	82 Occupations in non-medical healthcare, body care, wellness and medical technicians
	83 Occupations in education and social work, housekeeping, and theology
	84 Occupations in teaching and training
	91 Occupations in in philology, literature, humanities, social sciences, and economics
	94 Occupations in the performing arts and entertainment
Business services	61 Occupations in purchasing, sales and trading
	62 Sales occupations in retail trade
	71 Occupations in business management and organisation
	72 Occupations in financial services, accounting and tax consultancy
	73 Occupations in law and public administration
	92 Occupations in advertising and marketing, in commercial and editorial media design
IT	41 Occupations in mathematics, biology, chemistry and physics
	42 Occupations in geology, geography and environmental protection
	43 Occupations in computer science, information and communication technology
Commercial services	01 Armed forces personnel
	51 Occupations in traffic and logistics (without vehicle driving)
	52 Drivers and operators of vehicles and transport equipment
	53 Occupations in safety and health protection, security and surveillance
	54 Occupations in cleaning services

To provide additional information on how workers differ across the five occupational fields, Table 14 summarizes several worker characteristics of the sample individuals that are employed on June 30, 2011 in one of the surveyed firms: Most workers in (1) occupations that focus on the manufacture of products (*Production*) are skilled employees with vocational training who predominantly conduct routine manual tasks. (2) Person-related service occupations (*Personal Services*) are dominated by skilled employees with vocational training who conduct non-routine manual tasks and expert workers with university degrees who conduct non-routine analytic tasks. (3) Business-related service occupations (*Business Services*) are most often skilled workers with vocational training or university degrees who perform routine cognitive and non-routine analytic work tasks. (4) IT and natural science occupations (*IT*) have the largest proportions of specialists and experts, workers with university degrees, and non-routine analytic tasks. (5) Other occupations in commercial services (*Commercial Services*) consist mainly of helpers and skilled employees, among whom the share of workers without vocational training is the highest, and who predominantly conduct non-routine manual jobs.

Table 14: Composition of Workers across Occupational Fields

	Production (1)	Personal Services (2)	Business Services (3)	IT (4)	Commercial Services (5)
Share of workers by job requirements (in %):					
Helper/assistant	11.45	12.09	2.23	2.12	35.16
Skilled employee	65.98	55.69	74.55	25.62	60.19
Specialist	13.67	10.66	12.50	30.52	2.86
Expert	8.91	21.56	10.71	41.74	1.79
Share of workers by education (in %):					
No vocational training	9.67	7.87	4.81	4.51	17.43
Vocational training	79.14	73.94	76.07	50.14	77.52
University degree	11.19	18.18	19.13	45.35	5.05
Share of workers by tasks (in %):					
Non-routine analytic	13.28	25.28	24.40	75.50	19.55
Non-routine interactive	0.00	13.40	12.37	0.00	0.05
Routine cognitive	31.75	8.49	63.23	22.38	1.24
Routine manual	36.21	3.61	0.00	2.12	18.13
Non-routine manual	18.75	49.23	0.00	0.00	61.02
No. of individuals	63,106	41,876	42,283	10,491	14,958
*Share of workers by software use (in %):**					
Standard office programs	64.86	60.52	93.95	98.46	30.12
Specific programs	56.22	52.47	73.05	90.73	24.70
Programs with extended features	18.94	8.61	16.56	73.22	5.24
Writing own programs	5.66	0.34	1.56	41.77	0.91
No. of individuals	1,009	666	888	385	177

Notes: *Values for software stem from a representative survey among individuals that have been working in 2011 in one of the surveyed firms that are the basis for our main estimations and is described in Subsection 2.2. See Arntz et al. (2020) for a more detailed description of the representative individual survey. Figures are weighted with firm stratification weights.

A.2 Technology Adoption Definition

For the identification of our technology adoption measure, we conduct the following sequential four-step procedure. First, we classify a firm j as a s-adopter if it predominantly increases its s-technology share relative to other technologies:

$$s\text{-adopter} \Leftarrow \max\left(\Delta k_{j,s=1.0/2.0}, \Delta k_{j,s=3.0}, \Delta k_{j,s=4.0}\right) \tag{3}$$

where $s \in \{1.0/2.0, 3.0, 4.0\}$ indexes the technology level of the work equipment and $\Delta k_{j,s}$ defines the change in the work equipment between 2011 and 2016 $k_{js}^{t=2016} - k_{js}^{t=2011}$. This step assigns 58% of our survey firms into one of the three adoption groups.

Second, if a firm increases predominantly two technology classes to the same extent, the highest level of s-technology class determines the s-adoption status.

$$s\text{-adopter} \begin{cases} s = 4.0 & \text{if } \Delta k_{j,s=4.0} = \Delta k_{j,s=3.0} \quad \wedge \quad \Delta k_{j,s=4.0} > \Delta k_{j,s=1.0/2.0} \\ s = 4.0 & \text{if } \Delta k_{j,s=4.0} = \Delta k_{j,s=1.0/2.0} \quad \wedge \quad \Delta k_{j,s=4.0} > \Delta k_{j,s=3.0} \\ s = 3.0 & \text{if } \Delta k_{j,s=3.0} = \Delta k_{j,s=1.0/2.0} \quad \wedge \quad \Delta k_{j,s=3.0} > \Delta k_{j,s=4.0} \end{cases}$$

For example, if a firm increases simultaneously its share of 4.0- and 3.0-technologies to an equal extent and decreases its share in non-digital technologies, we consider this firm as 4.0-adopter. This step assigns an adoption status to another 5.6% of our survey firms.

Third, we classify a firm j as a s-adopter if s-technologies already made up the highest share of technologies in 2011, conditional on firms making no changes in the technology shares between 2011 and 2016. This step assigns 31.8% of our survey firms into one of the three adoption groups.

$$s\text{-adopter} \Leftarrow \max\left(k_{j,s=1.0/2.0}^{t=2011}, k_{j,s=3.0}^{t=2011}, k_{j,s=4.0}^{t=2011}\right) \quad \wedge \quad \Delta k_j = 0 \tag{4}$$

Fourth, if two technology classes are of equal size in 2011 and the firm does not change its technology shares between 2011 and 2016, the highest level of s-technology class determines the s-adoption status.

$$s\text{-adopter} \begin{cases} s = 4.0 & \text{if } k_{j,s=4.0}^{t=2011} > 0 \quad \wedge \quad \Delta k_j = 0 \\ s = 3.0 & \text{if } k_{j,s=3.0}^{t=2011} > 0 \quad \wedge \quad \Delta k_j = 0 \end{cases}$$

This step assigns the remaining 4.6% of our survey firms into one of the adoption groups.

A.3 Additional Results

A.3.1 Worker Composition

Table 15: Worker Characteristics of (Not) Employed Individuals at Adopting vs. Non-Adopting Firms

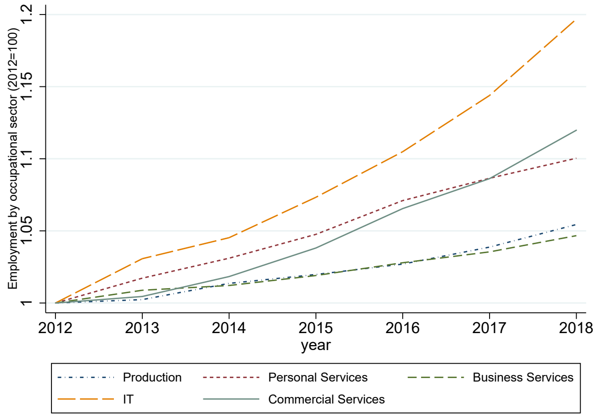
	Non-adopters		3.0-adopters		4.0-adopters	
Employment status in 2016:	Employed	Not Employed	Employed	Not Employed	Employed	Not Employed
Worker characteristics in 2011:	(1)	(2)	(3)	(4)	(5)	(6)
Age	40.74	42.53	42.22	42.43	41.28	42.20
Daily wage (in euros)	73.06	63.84	86.34	76.55***	91.02	81.05***
Share of workers by occupational fields (in %):						
Production	37.02	41.08	26.72	19.30***	28.90	25.24***
Personal services	27.71	24.41	27.28	32.94**	19.19	25.93
Business services	17.86	15.91	32.70	33.25***	38.40	32.36***
IT	0.75	4.89	2.43	1.93	4.14	3.59
Commercial services	16.66	13.71	10.87	12.58	9.37	12.88
Share of workers by job requirements (in %):						
Helper/assistant	16.18	14.88	9.01	11.98	10.86	16.51
Skilled employee	64.95	72.69	66.09	64.50**	61.21	55.92***
Specialist	6.68	5.61	11.75	10.25***	15.69	10.48***
Expert	12.19	6.82	13.15	13.27***	12.24	17.09***
Share of workers by education (in %):						
No vocational training	11.23	15.65	6.91	11.42	7.55	12.53
Vocational training	80.48	77.83	76.24	71.75	74.90	64.68**
University degree	8.29	6.52	16.85	16.83***	17.55	22.79***
No. of individuals	13,027	1,842	79,327	10,254	60,731	7,533

Notes: The figures represent average values across firms and are weighted with firm stratification weights. Columns (1), (3), and (5) contain workers still employed on June 30, 2016 at either the original employer or at a different employer. Columns (2), (4) and (6) contain individuals who are not employed anymore on June 30, 2016. Columns (4) and (6) show significance levels from mean comparisons of no longer employed individuals of adopting firms to non-adopters (Column 2) based on t-tests. Significance levels: * 10%, ** 5%, *** 1%.

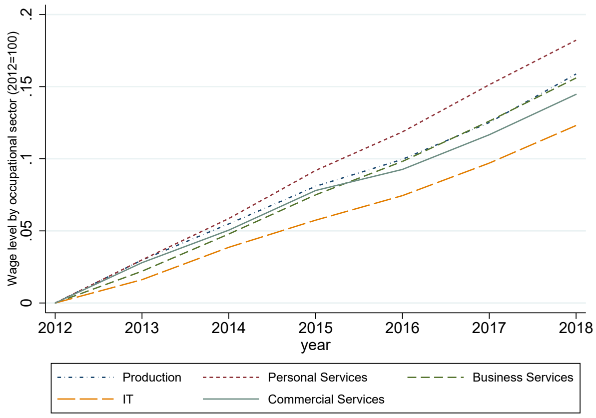
A.3.2 Aggregated Labor Market Trends

Figure 6: Occupational Employment and Wage Trends in the German Workforce (2012-2018)

(a) Employment Level (2012=100)



(b) Wage Level (2012=100)



Notes: Panel (a) shows the employment and Panel (b) the wage trends by occupational fields as defined in Appendix Subsection A.1.3. Figures are based on the entire worker population employed subject to social security contributions on June 30 of each year. Daily wages are measured in nominal terms and refer to full-time workers.

A.3.3 Employment Stability

Table 16 differentiates the total number of days individuals are not regularly employed, days in unemployment, irregular employment and out of labor force. Irregular employment includes, for example, marginal employment, apprentices, and partial retirement contracts. Table 16 displays that 3.0-adoption statistically significantly reduces the accumulated number of days in irregular employment (Columns 5-6). Since all individuals are regularly employed on June 30 in 2011, the fewer cumulative days in irregular employment until 2016 of workers initially employed at 3.0-adopter firms confirms the enhanced employment stability compared to workers of non-adopting firms. The status out of labor force refers to the economically inactive population and includes employment not registered in the social security data as self-employment, civil servants, and military services. Table 16 documents that 4.0-adoption reduces the days out of labor force (Columns 7-8), although the coefficient is only significant at the 10% significance level. Taken together, the additional analysis suggests that technology adoption enhances individuals' employment stability.

Table 16: Adjustments in Workers' Employment Stability to Firms' Technology Investments - Decomposition of Not Employed into Unemployed, Irregular Employed and Out of Labor Force

Dependent variable: number of accumulated days (after 5 years)..								
	not employed		unemployed		irregular employed		out of labor force	
	(A)+(B)+(C)		(A)		(B)		(C)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
3.0-adopters	-82.45***	-48.97***	-33.07***	-11.74	-22.74**	-14.49***	-26.65	-22.74
	(-3.03)	(-2.90)	(-3.53)	(-1.50)	(-2.31)	(-2.76)	(-1.48)	(-1.49)
4.0-adopters	-63.51**	-31.45	-14.46	2.86	-15.12	-6.18	-33.92*	-28.13*
	(-2.22)	(-1.63)	(-1.21)	(0.25)	(-1.47)	(-1.01)	(-1.87)	(-1.74)
Ind. cov.		✓		✓		✓		✓
Firm cov.		✓		✓		✓		✓

Notes: N=172,714. All models are estimated with OLS based on the cross-sectional data and weighted with firm stratification weights. Subsection 4.1 describes the individual- and firm-level covariates. Columns (1-2) display the accumulated days between 2011 and 2016 that individuals are not employed in regular employment. Columns (3-4) refer to the accumulated days in which individuals receive any type of social security benefits. Irregular employment (Columns 5-6) includes marginal employment, apprentices and partial retirement contract workers. Out of labor force (Columns 7-8) refers to the economically inactive population but also includes employment states that are not registered in the administrative social security data, for example self-employment, civil servants, and workers in the military service. Robust standard errors are clustered at the firm level. t-statistics in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

Table 17: Adjustments in Workers' Employment Stability to Firms' Technology Investments - Alternative Technology Adoption Measures

Dependent variable: number of accumulated days (after five year)..									
	..employed at original employer			..employed at different employer			..unemployed		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
A. Alternative Technology Adoption Measure With Alternative Weighting δ									
All Firms (N=172,714)									
3.0-adopters	134.23**	69.49**	72.68**	-52.38	-17.36	-26.20	-37.19***	-21.16***	-17.25**
	(2.40)	(2.40)	(2.46)	(-1.52)	(-0.74)	(-1.09)	(-3.68)	(-2.75)	(-2.14)
4.0-adopters	71.77	22.62	27.20	-6.36	16.21	6.03	-17.93	-4.65	-2.02
	(1.20)	(0.70)	(0.84)	(-0.16)	(0.57)	(0.21)	(-1.43)	(-0.48)	(-0.18)
B. Alternative Technology Adoption Measure Without Weighted Aggregation									
B1. Service Providers (N=98,482)									
3.0-adopters	152.00*	82.93*	83.02**	-59.87	-30.65	-31.55	-28.62*	-7.71	-4.21
	(1.68)	(1.89)	(1.98)	(-1.10)	(-0.85)	(-0.89)	(-1.95)	(-0.75)	(-0.40)
4.0-adopters	79.72	27.83	35.85	2.16	18.95	8.97	-14.30	3.93	8.97
	(0.85)	(0.58)	(0.79)	(0.04)	(0.46)	(0.22)	(-0.83)	(0.33)	(0.63)
B2. Manufacturers (N=74,232)									
3.0-adopters	100.68***	77.62***	45.23*	-50.60**	-36.89*	-26.67	-26.73***	-21.45***	-17.37**
	(3.32)	(2.89)	(1.88)	(-2.15)	(-1.75)	(-1.30)	(-2.88)	(-2.87)	(-2.53)
4.0-adopters	95.06***	59.48*	14.45	-54.90**	-40.87*	-19.81	-22.90**	-13.44	-11.46
	(2.70)	(1.94)	(0.46)	(-2.24)	(-1.86)	(-0.86)	(-2.33)	(-1.59)	(-1.51)
Ind. cov.		✓	✓		✓	✓		✓	✓
Firm cov.			✓			✓			✓

Notes: All models are estimated with OLS based on the cross-sectional data and weighted with firm stratification weights. Subsection 4.1 describes the individual- and firm-level covariates. This table shows results for alternative technology adoption measures analogous to the main results of Table 4. Robust standard errors are clustered at the firm level. t-statistics in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

A.3.4 Wage Growth

Table 18: Adjustments in Workers' Wage Growth to Firms' Technology Investments - Alternative Technology Adoption Measures

Dependent variable: (five year) 100 ×Δ in log daily wage of workers..						
	..employed at original employer (stayers)			..employed at different employer (switchers)		
	(1)	(2)	(3)	(4)	(5)	(6)
A. Alternative Technology Adoption Measure With Alternative Weighting δ						
All Firms (N=113,704)						
3.0-adopters	1.70	1.54	2.17*	-14.20*	-10.59**	-11.22***
	(1.21)	(1.11)	(1.80)	(-1.95)	(-2.11)	(-2.69)
4.0-adopters	2.75**	2.40**	2.48*	-15.43*	-12.47**	-14.65***
	(2.32)	(2.10)	(1.78)	(-1.96)	(-2.26)	(-3.03)
	N=88,363			N=25,341		
B. Alternative Technology Adoption Measure Without Weighted Aggregation						
B1. Service Providers (N=54,920)						
3.0-adopters	3.92**	2.79	4.54***	-22.02**	-16.68**	-15.73***
	(2.12)	(1.24)	(2.68)	(-2.10)	(-2.36)	(-2.66)
4.0-adopters	5.91***	4.35**	5.31**	-25.22**	-20.30***	-20.04***
	(3.70)	(2.14)	(2.48)	(-2.30)	(-2.70)	(-3.14)
	N=39,316			N=15,604		
B2. Manufacturers (N=58,784)						
3.0-adopters	-1.08	-0.70	-0.54	-4.49	-4.50**	-2.70
	(-0.74)	(-0.60)	(-0.51)	(-1.63)	(-2.08)	(-1.26)
4.0-adopters	-1.21	-1.09	-0.69	-7.24**	-5.93**	-2.68
	(-0.77)	(-0.79)	(-0.55)	(-2.04)	(-2.35)	(-1.12)
	N=49,047			N=9,737		
Ind. cov.		✓	✓		✓	✓
Firm cov.			✓			✓

Notes: All models are estimated with OLS based on the cross-sectional data and weighted with firm stratification weights. Subsection 4.1 describes the individual- and firm-level covariates. The coefficients are multiplied by 100 to represent percentage point differences between 3.0- or 4.0-adopters compared to non-adopters. This table shows results for alternative technology adoption measures analogous to the main results of Table 5. Robust standard errors are clustered at the firm level. t-statistics in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

Fixed-Effects Estimates. The main wage growth results (Panel A of Table 5) relate to the wage growth differential from 2011 to 2016 between the three adoption groups, controlling for initial period individual- and firm-level characteristics. As a robustness check, we include observations of the intermediate years 2012 to 2015 and estimate fixed effects models. The dependent variable is workers' log daily wage and as control variables we only include time-varying characteristics. The coefficients measure the average annual deviation from the time trend (which captures the wage growth of non-adopters). To account for serial correlation, we cluster standard errors at the firm level. Table 19 shows the results. The coefficients for stayers are positive for both 3.0- and 4.0-technology adoption, however only the latter is significant at the 5% significance level. Since the coefficients capture average annual deviations, one has to multiply them with the factor 5 (for the years 2011 to 2016) to compare them with the main wage results of Table 5. Doing so, the 4.0-adoption coefficient controlling for individual- and firm-level covariates in Column (3) is $0.51 \times 5 = 2.55$, that is very close to the corresponding coefficient in Panel A of Table 5 (+2.67). For switchers we detect negative deviations from the wage growth of non-adopters, which are in line with Table 5 (Columns 4-6). Taken together, the fixed effect estimates confirm the robustness of the main wage growth results.

Table 19: Adjustments in Workers' Wage Growth to Firms' Technology Investments - Fixed Effects Models

Dependent variable: 100 × log daily wage of workers..						
	..employed at original employer (stayers)			..employed at different employer (switchers)		
	(1)	(2)	(3)	(4)	(5)	(6)
3.0-adopters	0.16	0.30	0.31	-1.27	-1.18	-1.05
	(0.53)	(1.09)	(1.14)	(-1.42)	(-1.30)	(-1.31)
4.0-adopters	0.43*	0.51*	0.51**	-1.46	-1.43	-1.31
	(1.68)	(1.96)	(1.99)	(-1.38)	(-1.34)	(-1.29)
Ind. cov.		✓	✓		✓	✓
Firm cov.			✓			✓
No. of individuals	88,363			25,341		

Notes: All models are estimated with fixed effects models based on yearly panel data and weighted with firm stratification weights. Time-varying individual-level characteristics include education, tenure, and foreigner status. Time-varying firm-level characteristics include firm size, sector and federal state. Subsection 4.1 defines the covariates. The coefficients are multiplied by 100 to represent percentage point differences between 3.0- or 4.0-adopters compared to non-adopters. Robust standard errors clustered at the firm level. t-statistics in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

A.4 Heterogeneous Adjustments

A.4.1 Occupational Fields

Table 20: Heterogeneous Worker Adjustments by Occupational Fields - Estimation Results

	Production (1)	Personal Services (2)	Business Services (3)	IT (4)	Commercial Services (5)
A. Accumulated days employed at original employer					
3.0-adopters	105.90***	7.57	17.96	235.98**	26.50
	(3.16)	(0.15)	(0.40)	(2.22)	(0.51)
4.0-adopters	15.68	25.94	-15.58	286.43***	-44.12
	(0.42)	(0.48)	(-0.31)	(2.64)	(-0.75)
B. Accumulated days employed at different employer					
3.0-adopters	-27.65	-4.41	7.47	69.52	-30.10
	(-0.93)	(-0.11)	(0.20)	(1.13)	(-0.63)
4.0-adopters	53.70	-32.61	30.17	35.05	-14.10
	(1.32)	(-0.68)	(0.71)	(0.58)	(-0.27)
C. Accumulated days unemployed					
3.0-adopters	-36.90***	-6.94	-14.48	8.01	12.55
	(-4.69)	(-0.58)	(-0.77)	(0.83)	(0.75)
4.0-adopters	-34.02***	9.91	5.31	1.16	40.52**
	(-3.66)	(0.70)	(0.24)	(0.13)	(2.08)
No. of individuals	63,106	41,876	42,283	10,491	14,958
D. Change in log daily wages (stayers)					
3.0-adopters	1.09	6.43***	5.57	2.85	0.36
	(1.11)	(2.79)	(1.21)	(1.03)	(0.12)
4.0-adopters	1.46	6.61***	5.67	7.01**	0.45
	(1.37)	(3.11)	(1.08)	(2.56)	(0.21)
No. of individuals	41,634	13,612	19,432	6,060	7,625
E. Change in log daily wages (switchers)					
3.0-adopters	-6.88	-10.80**	-0.17	-12.26*	-3.22
	(-1.52)	(-2.36)	(-0.04)	(-1.78)	(-0.52)
4.0-adopters	-11.82**	-6.30	-3.40	-6.85	-8.65
	(-2.32)	(-1.15)	(-0.84)	(-1.01)	(-1.18)
No. of individuals	9,791	4,107	6,898	2,255	2,290

Notes: All models are estimated with OLS based on the cross-sectional data and weighted with firm stratification weights. Subsection 4.1 describes the individual- and firm-level covariates. The table shows the more detailed results of Figure 2. The coefficients of Panel D and E are multiplied by 100 to represent percentage point differences between 3.0- or 4.0-adopters compared to non-adopters. Robust standard errors are clustered at the firm level. t-statistics in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

A.4.2 Job Requirements

Table 21: Heterogeneous Worker Adjustments by Job Requirements - Estimation Results

	Helper/ assistant (1)	Skilled employee (2)	Specialist (3)	Expert (4)
A. Accumulated days employed at original employer				
3.0-adopters	42.00	52.86*	3.30	157.31**
	(1.00)	(1.81)	(0.06)	(2.56)
4.0-adopters	-98.90*	35.91	-66.35	120.04*
	(-1.79)	(1.13)	(-1.23)	(1.95)
B. Accumulated days employed at different employer				
3.0-adopters	-18.45	2.27	14.38	-145.68***
	(-0.57)	(0.10)	(0.35)	(-2.73)
4.0-adopters	61.75	2.51	96.03**	-127.49**
	(1.32)	(0.10)	(2.08)	(-2.26)
C. Accumulated days unemployed				
3.0-adopters	-14.83	-14.28	-1.92	-3.51
	(-0.97)	(-1.40)	(-0.25)	(-0.43)
4.0-adopters	4.76	2.98	4.84	-0.29
	(0.29)	(0.20)	(0.65)	(-0.03)
No. of individuals	18,580	98,873	27,803	27,458
D. Change in log daily wages (stayers)				
3.0-adopters	-0.10	1.97	6.33***	3.64*
	(-0.05)	(1.31)	(3.25)	(1.93)
4.0-adopters	0.71	2.35	5.46***	3.65*
	(0.44)	(1.33)	(2.99)	(1.75)
No. of individuals	9,018	50,080	15,745	13,520
E. Change in log daily wages (switchers)				
3.0-adopters	6.24	-9.73**	3.10	-4.44
	(1.36)	(-2.11)	(0.95)	(-1.31)
4.0-adopters	0.33	-15.27***	0.39	-2.16
	(0.07)	(-2.96)	(0.12)	(-0.53)
No. of individuals	2,005	13,501	4,420	5,415

Notes: All models are estimated with OLS based on the cross-sectional data and weighted with firm stratification weights. Subsection 4.1 describes the individual- and firm-level covariates. The table shows the more detailed results of Figure 3. The coefficients of Panel D and E are multiplied by 100 to represent percentage point differences between 3.0- or 4.0-adopters compared to non-adopters. Robust standard errors are clustered at the firm level. t-statistics in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

A.4.3 Tasks

Table 22: Heterogeneous Worker Adjustments by Tasks - Estimation Results

	Non-routine analytic (1)	Non-routine interactive (2)	Routine cognitive (3)	Routine manual (4)	Non-routine manual (5)
A. Accumulated days employed at original employer					
3.0-adopters	188.73***	18.14	43.39	65.00	-13.82
	(3.26)	(0.24)	(1.02)	(1.42)	(-0.36)
4.0-adopters	136.33**	-51.95	-9.77	25.11	-8.43
	(2.26)	(-0.68)	(-0.21)	(0.49)	(-0.19)
B. Accumulated days employed at different employer					
3.0-adopters	-102.19**	-43.97	13.52	-22.53	12.30
	(-2.27)	(-0.58)	(0.38)	(-0.60)	(0.41)
4.0-adopters	-78.21	-36.34	76.93*	-21.03	-10.97
	(-1.61)	(-0.48)	(1.83)	(-0.52)	(-0.29)
C. Accumulated days unemployed					
3.0-adopters	4.31	40.22	-34.91***	-12.55	-11.58
	(0.50)	(1.29)	(-2.75)	(-1.00)	(-0.89)
4.0-adopters	11.07	117.27***	-33.53**	1.75	-2.92
	(1.04)	(3.30)	(-2.57)	(0.13)	(-0.16)
No. of individuals	46,753	6,941	48,823	37,209	32,988
D. Change in log daily wages (stayers)					
3.0-adopters	4.44***	-2.42	4.80	1.24	2.57
	(2.93)	(-0.30)	(1.61)	(0.97)	(1.44)
4.0-adopters	4.33***	-0.86	3.76	1.96	3.58*
	(2.84)	(-0.09)	(1.21)	(1.51)	(1.85)
No. of individuals	24,453	2,121	25,211	24,050	12,528
E. Change in log daily wages (switchers)					
3.0-adopters	-10.26***	-1.96	-16.39***	7.96***	-0.58
	(-2.81)	(-0.33)	(-4.63)	(2.86)	(-0.14)
4.0-adopters	-10.24**	-9.08	-21.48***	4.57	-2.05
	(-2.44)	(-1.61)	(-4.99)	(1.39)	(-0.47)
No. of individuals	8,464	764	7,261	5,998	2,854

Notes: All models are estimated with OLS based on the cross-sectional data and weighted with firm stratification weights. Subsection 4.1 describes the individual- and firm-level covariates. The table shows the more detailed results of Figure 4. The coefficients of Panel D and E are multiplied by 100 to represent percentage point differences between 3.0- or 4.0-adopters compared to non-adopters. Robust standard errors are clustered at the firm level. t-statistics in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

A.4.4 Education

Table 23: Heterogeneous Worker Adjustments by Education - Estimation Results

	No vocational training (1)	Vocational training (2)	University degree (3)
A. Accumulated days employed at original employer			
3.0-adopters	49.58	63.47**	22.61
	(0.98)	(2.18)	(0.48)
4.0-adopters	-66.18	30.91	7.94
	(-1.09)	(0.92)	(0.16)
B. Accumulated days employed at different employer			
3.0-adopters	-23.90	-7.52	-34.89
	(-0.72)	(-0.27)	(-0.88)
4.0-adopters	47.34	22.40	-68.90
	(1.24)	(0.65)	(-1.64)
C. Accumulated days unemployed			
3.0-adopters	-18.27	-15.40**	-0.01
	(-1.15)	(-1.97)	(-0.00)
4.0-adopters	2.20	-9.64	42.88**
	(0.13)	(-1.01)	(2.05)
No. of individuals	11,763	123,684	37,267
D. Change in log daily wages (stayers)			
3.0-adopters	-5.36*	4.09***	0.49
	(-1.72)	(3.46)	(0.21)
4.0-adopters	-0.86	3.42***	2.77
	(-0.29)	(2.77)	(1.09)
No. of individuals	5,619	65,016	17,728
E. Change in log daily wages (switchers)			
3.0-adopters	-5.09	-7.97*	-3.82
	(-0.69)	(-1.96)	(-1.09)
4.0-adopters	-4.22	-12.75***	-6.11
	(-0.56)	(-2.64)	(-1.42)
No. of individuals	1,439	16,190	7,712

Notes: All models are estimated with OLS based on the cross-sectional data and weighted with firm stratification weights. Subsection 4.1 describes the individual- and firm-level covariates. The table shows the more detailed results of Figure 5. The coefficients of Panel D and E are multiplied by 100 to represent percentage point differences between 3.0- or 4.0-adopters compared to non-adopters. Robust standard errors are clustered at the firm level. t-statistics in parentheses. Significance levels: * 10%, ** 5%, *** 1%.