The Impact of Investments in New Digital Technologies on Wages – Worker-level Evidence from Germany

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Abstract

The strong rise of digitalisation, automation, machine learning and other related new digital technologies has led to an intense debate about its societal impacts. Especially the transitions of occupations and the effects on labor demand and workers' wages are still open questions. Research projects dealing with this issue are often facing a lack of data on the usage of new digital technologies. This paper uses a novel linked employer-employee data set that contains detailed information on firms' technological upgrading between 2011 and 2016, a recent period of rapid technological progress. We are the first developing a digital tools index based on the German expert database BERUFENET. The new index contains detailed information on the work equipment that is used by the workers. Hence, we observe the degree of digitalisation at both sides, the firm and the worker level. The data allow us to investigate the impact of technology investments on the remuneration of employees within firms.

Overall, the results from individual level fixed effects estimates suggest that investments in new digital technologies on the firm level positively affect wages of the firms' workers. Sector-specific results show that investments in new digital technologies increase wages in knowledge-intensive services and non-knowledge-intensive production firms. The wage growth effects of employees in 'digital pioneer' firms relative to the specific reference group of workers in 'digital latecomer' firms are most pronounced for low- and medium-educated workers. This result indicates that workers, who are often perceived as the losers of the digital transformation (mostly in terms of employment) might nevertheless benefit in terms of wages.

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1 Introduction

In recent years, the ongoing digitization[1] and automation as well as advances in machine learning and mobile robotics have raised concerns that human employment will be more and more substituted by computers, algorithms or robots. New digital technologies increasingly undertake tasks which were performed by human beings in the past (Brynjolfsson and McAfee, 2014). Frey and Osborne (2017) estimate that 47 percent of US employment is threatened by computer controlled smart machines. Although this anxiety appears exaggerated (see, for instance, Autor, 2015; Arntz et al. 2017a, Dengler and Matthes, 2015), an increasing number of studies address the labor market consequences of modern automation technologies.

In the past, the empirical literature - namely the tasks based approach - has shown that computerization mostly affects repetitive, routine tasks predominantly used which are mainly performed by medium-skilled occupations (Autor et al., 2003; Autor, 2013; Autor and Dorn, 2013). These tasks are substituted, while non-routine cognitive tasks predominantly used in high-skill occupations are complemented by computerization.[2] This means that employment in occupations at the bottom and the top of the skill distribution increases more strongly than in medium-ranked occupations. This polarization of employment has been detected for many industrialized countries in the last two decades (Goos et al., 2014; Michaels et al., 2014; Dustmann et al., 2009; Autor et al., 2006).

In contrast to previous years, the ongoing digitization might affect jobs of high-skilled workers as much as jobs of skilled or low-skilled workers (Frey and Osborne, 2017). Up to now, this hypothesis has not finally been proofed by the empirical literature. The principal reason for this is a lack of data on the usage of new digital technologies like analytical tools for analyzing big data, cloud computing systems, internet platforms, cyber-physical/ embedded systems or the internet of things.[3] Besides the change of job tasks, the existing literature discusses the effects of the diffusion of industrial robots on the employment of workers. Depending on the aggregation level – occupation, industry, country or region – and the focus of the study, the estimated effects are positive or negative. For instance, Acemoglu and Restrepo (2017) find a negative effect of the diffusion of robots on employment at the regional level. On the contrary, Graetz and Michaels (2015) do not detect negative effects of industrial robots for a number of developed countries. Dauth et al. (2017) find that the diffusion of robots decreases employment in the manufacturing sector. But they point to the fact that this decrease is fully offset by an increase in service jobs. Since industrial robots are actually not new, however, the effects of new digital technolo-

[1] The term digitisation (or digitalisation, respectively) originally describes the conversion of analog to digital information in a technical sense (Negroponte, 1995). In our understanding, digitisation stands for the transformation of the economy through new digital technologies like big data analytics, embedded systems, smart factories, artificial intelligence and many more (see Loebbecke and Picot, 2015).

[2] For a systematic discussion, see Acemoglu and Autor (2011).

[3] By contrast, there is a large number of studies dealing with the impact of –established– information and communication technologies (including computers) on the productivity of firms (see Basker, 2012; Bloom et al., 2012; Doms et al. 2004; Brynjolfsson and Hitt, 2000) and industries (see Stiroh, 2002; Acemoglu et al. 2014).

gies are unclear. A first study that directly investigates the impact of new digital technologies on employment is Arntz et al. (2017b). They use direct measures of technological adoption from a firm-level survey to explore the job creation and job destruction channels in firms. First results suggest positive employment effects of investments into new digital technologies.

Turning to the effect of new technologies on wages, the empirical evidence also refers to tasks or to the usage of industrial robots. For instance, Acemoglu and Restrepo (2017) find negative wage effects of industrial robots, the results of Graetz and Michaels (2015) suggest positive effects on wages. Dauth et al. (2017) study the impact of rising robot exposure on the careers of individual manufacturing workers. They detect a negative impact of robots on individual earnings arising mainly for medium-skilled workers in machine-operating occupations, while high-skilled managers gain. A prominent study that is not dealing with industrial robots is Akerman et al. (2015). According to their findings, the access to broadband internet improves the labor market outcomes and productivity of skilled workers and worsens it for unskilled workers. Altogether, the lack of data concerning the usage of new digital technologies is prevalent with regard to the wage literature.

Our study overcomes this problem. Like Arntz et al. (2017b), we use a novel data set which was developed by linking the "IAB-ZEW Labour Market 4.0" establishment survey with employment biographies from social security records, the IAB establishment panel and data derived from text mining of the occupational database BERUFENET. This novel linked employer-employee data set contains, among others, detailed information on firms' upgrading of new digital technologies between 2011 and 2016, and detailed information on the work equipment that is used by the workers within the firm. Hence, we observe the degree of digitalisation at both sides, the firm and the worker level. The data allow us to investigate the impact of technology investments on the remuneration of the employees within firms.

Overall, the results from individual level fixed effects estimates suggest that firms' investments in new digital technologies do not affect the wages of their workers negatively. Sector-specific results show that investments in new digital technologies increase wages for workers employed in knowledge-intensive services and non-knowledge-intensive production firms. The wage growth effects of employees in 'digital pioneer' firms relative to the specific reference group of workers in 'digital latecomer' firms are most pronounced for low and medium-educated workers. This indicates that workers, who are often perceived as the losers of the digital transformation (mostly in terms of employment) do nevertheless benefit in terms of wages.

The remainder of the paper is organized as follows: the next section deals with a description of our data source and the selection of our sample. Section 3 describes the estimation approach and presents the results. Section 4 concludes.

2 Data, sample selection and some descriptives

For our empirical analyses, we use a novel data set which was developed by linking the ’IAB-ZEW Labour Market 4.0‘ establishment survey with employment biographies from social security records and additional information from BERUFENET and the IAB Establishment Panel.

Establishment survey: The ‘IAB-ZEW Labour Market 4.0’ establishment survey on the use and importance of new digital technologies is a representative survey of establishments in Germany[4]. About 2,000 establishments have participated in the survey in 2016. The sample was drawn from the establishment data file of the IAB. It was stratified by four firm size categories, East and West Germany and five sector categories differentiating between: 1. non-knowledge intensive manufacturing (e.g. furniture producers, building firms), 2. knowledge intensive manufacturing (e.g. car manufacturers, machine manufacturers), 3. non-knowledge intensive services (e.g. wholesalers, restaurants), 4. knowledge intensive services (e.g. scientific services, banks, insurances) and 5. information and communication technologies (ICT) (producer of data processing equipment, consumer electronics or telecommunications equipment, enterprises that provide services in information technology, telecommunication or data processing). While the basic differentiation is between producers and service firms, the ICT-sector (where both producers and service firms are included) is viewed separately because of its central role as a technology-hub and core enabler for a digitalized economy. The technical managers and experts of the establishments were asked to categorize production technologies (PT) on the one hand and office and communication technologies (OCT) on the other hand into 3 different classes (see Table 1). The higher the class, the higher is the degree of digitization.

Table 1: Categorization of PT and OCT into three classes with increasing degree of digitization / automation

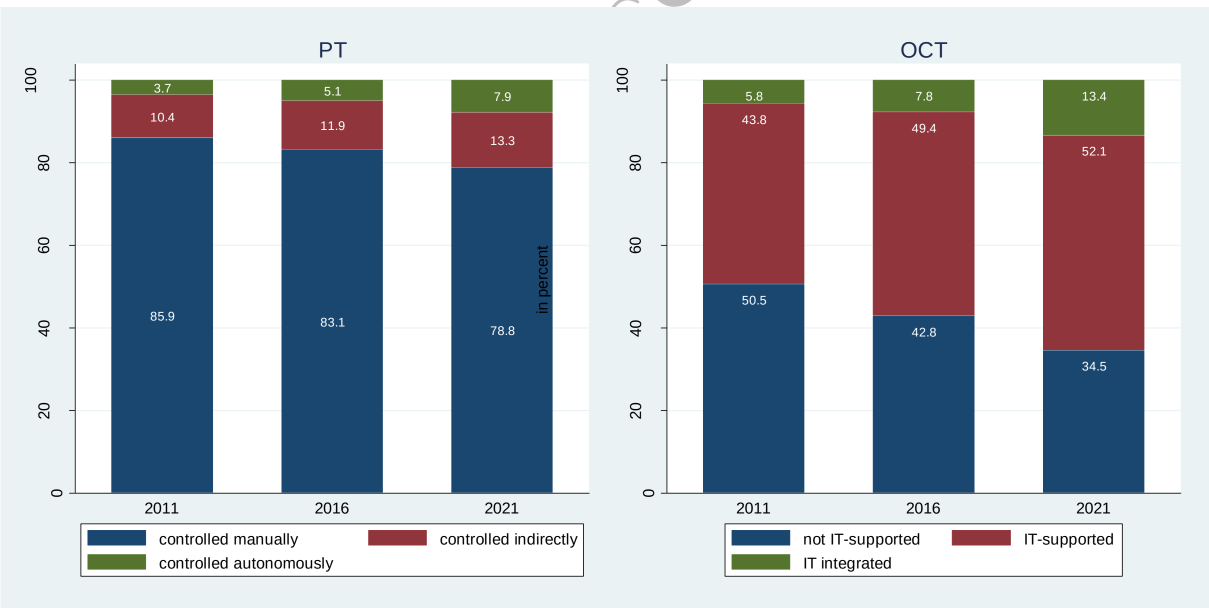
Dig. Tech. Class	Production technologies (PT)	Office and communication technologies (OCT)
1	**PT 1: controlled manually by human beings,** e.g. drilling machines, cars, X-ray machines.	**OCT 1: not IT-supported,** e.g. phones, copier, fax machines.
2	**PT 2: controlled indirectly/partly by human beings,** e.g. CNC-machines, industrial robots.	**OCT 2: IT-supported,** e.g. computer, terminals, electronic cash registers or CAD-systems.
3	**PT 3: controlled autonomously by machines.** Modern production systems like ’smart factories‘, ’cyber-physical/ embedded systems‘ and ’internet of things‘. Machines / computers that operate to a large part or fully autonomously and automatically.	**OCT 3: IT-integrated,** e.g. analytical tools using big data, cloud computing systems, Internet platforms, Shop-systems or online- markets. Machines/ computers that operate to a large part or fully autonomously and automatically.

[4] Due to data protection requirements, these new data are not yet available to the scientific community. But a scientific use file (SUF) will be provided in the medium run by the Research Data Center (FDZ) of the German Federal Employment Agency at the IAB (see http://fdz.iab.de).

PT 3 can be seen as new digital production technology (in Germany also called industry-4.0-technology), OCT as new digital office and communication technologies (in Germany also called services-4.0-technology). In 2016, the establishments were asked for the current status as well as for the status five years ago and the expected status in the future (in five years). Collating these statuses' information, we are able to identify temporal changes. If the share of PT 3 and/ or OCT 3 within the establishment increases over time, this is a clear indication of investments in new digital technologies. It is important to know that producers usually use both, PT and OCT while some service firms use OCT, only.

Figure 1 shows that the share of new digital technologies (both industry-4.0- and services-4.0-technologies) is still very limited. On average, 5.1 percent of PT and 7.8 percent of OCT can be assigned to new digital technologies. The degree of IT-supported OCT (49.4 percent) is also distinctly higher than the share of indirectly controlled PT (11.9 percent). Due to the 'natural' high volume of digital technologies in OCT, the share of non-IT-supported technologies is much lower (42.8 percent) than the corresponding group of manually controlled PT (83.1 percent). In both PT and OCT, there is a slight trend toward IT-supported and indirectly controlled technologies, but this trend seems to evolve rather slowly.

Figure 1: Trends in automation level of firms' work equipment



Based on this categorization and further information provided by the survey[5], we differentiate the groups of establishments: Pioneer firms in digital technologies ('digital pioneers', or for short 'pioneers') already use new digital technologies and have invested in new digital technologies between 2011 and 2016. For this group of firms the degree of IT-supported OCT increased from 12.5 percent in 2011 to 25.1 percent

[5] Besides the categorization of PT and OCT, the managers /production managers of the firm were generally asked whether *'the usage of new digital technologies is a topic in the establishment'*. 31 percent answered *'no, we haven't yet considered the usage of new digital technologies*', 15 percent, answered, *'we don't use these technologies at the moment, but we already deal with the topic'*, 2 percent said *'we don't use these technologies at the moment, but we already plan an investment*', 34 percent said *'we already use these technologies'* and 18 percent answered *'the usage of these technologies is an essential part of our business'* (see also Arntz et al. 2016)

in the year 2016, the degree of autonomously controlled PT from 7.2 percent to 13.7 percent, respectively (see Appendix Figure A1). 'Digital latecomers' (or for short 'latecomers') are defined as firms who indicate that they do not use new digital technologies; accordingly, the share of new digital technologies in the year 2016 is 0 percent, (see Appendix Figure A1). The third group –the 'digital peloton' or short 'peloton'– gathers the remaining establishments. The average degree of 4.0-technologies in the year 2016 is about 6 percent for both, OCT and PT (see Appendix Figure A1). This differention leads to 383 latecomers (19 percent of the establishments in the sample), 1.340 peloton firms (66 percent) and 309 pioneers (15 percent) in our data set.

Employment histories: Next, we link the survey data to employment biographies from social security records (Beschäftigten-Historik, BeH) of all workers employed in the surveyed firms between 2011-2016. The BeH covers the majority of the German workforce and is representative of dependent workers.[6] It contains important personal characteristics (sex, age, education, nationality, job status, occupation) as well as information on region, industry, and wages. Because the BeH is derived from mandatory employer notifications to the German social security system, the data are highly accurate and reliable.

Despite of this strengths, the BeH suffers from some moderate limitations: firstly, earnings are top-coded in the data. For this reason, we estimate censored regressions for each year (we use age, education, establishment size, occupation, firms' foreigner share, region and type of the region as covariates) separated for male and female workers and impute the censored wages. We follow the procedure described in Dustmann at al. (2009, p. 877), but we include more covariates than they do in their baseline imputation model. The wages are then deflated to 2010 prices. Secondly, working time is only reported in three categories: full-time, part-time with at least 50 percent of full-time working hours and part-time with less than 50 percent. To avoid bias due to imprecise information on working time, we restrict our analysis to full-time working (16-65 year-old) men and women, excluding apprentices, trainees and working students. Thirdly, data show to some extent inconsistencies (or missing data) with regard to workers' formal education. We apply a basic version of the approach proposed by Fitzenberger et al. (2006) and impute the information concerning education according to the information available in preceeding or subsequent spells of the individuals' employment history. Lastly, we exclude observations with dubious wage information below a specific time-varying threshold.[7] Focusing on employment spells overlapping June 30th of a year, our sample selection leaves about 1.1 million worker-year observations.

The aim of our study is to investigate how workers' wages are affected by the firm investments in new digital technologies. Because the survey provides results on the changes of technologies between 2011 and 2016, but do not include the exact dates of the technology investments, we focus on workers being

6 The BeH dataset excludes only self-employed, civil servants, individuals in (compulsory) military service, and - before the year 1999 - individuals in jobs with no more than 15 hours per week or temporary jobs that last no longer than 6 weeks.

[7] The so-called marginal wages threshold is a nominal daily wage of 13.15 € in the year 2011 and 14.79 € in 2016. Less than 1 percent of the observations are dropped when applying this threshold.

employed in both years 2011 and 2016. That is, we create a balanced panel of male and female establishment stayers. This allows us to measure the wage effects of establishment stayers in a meaningful way, but as a consequence the paper remains silent about wage effects for firm leavers and firms' new entrants (and also about wage effects for part-time workers). We are aware that our sample probably might be a positive selection of workers. We discuss this issue below. Altogether, we observe in each year 90,982 male and female full-time workers in 1,525 firms.[8]

BERUFENET: The data source from which we identify digital tools is the BERUFENET, an online expert database of the Federal Employment Agency[9]. The BERUFENET offers detailed information about every single occupation, e.g. about occupational and vocational training contents, tasks, tools, entrance requirements, earnings and employment perspectives. The occupations are based on the German classification of occupations (Klassifikation der Berufe 2010, KldB2010). The key section of the BERUFENET for the means of this paper is the section on work items / tools (in German: 'Arbeitsgegenstaende').[10] We use a unique BERUFENET data extract of the Federal employment agency. This extract facilitates analyses of tools for 2,963 occupations. The definition of tools in BERUFENET is very broad and covers about 14,333 tools. After selecting suitable tools for further analysis we use 5,919 of them. Janser (2018) describes the database in more detail.

We devide the tools into three categories:

1. IT-aided tools are electronically based tools, such as computers, printers, electronic machines, that are not explicitly dedicated to an industry 4.0 feature (which is covered by category 2).

2. IT-integrated tools are electronically based AND are explicitly dedicated to an industry 4.0 or services 4.0 feature, such as 3D printers, machine learning software or mobile robot clusters.

3. Non-IT tools are not covered by categories 1 and 2. By definition these tools comprise a very broad range of different tools.

Given the large number of potential tools, we have chosen a semi-automatic text mining approach to identify digital tools. The procedure is based on a text mining approach introduced by Janser (2018). He applies a comprehensive catalog of digital tool keywords and regular expression algorithms to identify those BERUFENET tools that are IT-aided or IT-integrated.

Table 2 shows the frequency of keywords and the results after the text mining with automatic coding. Overall 279 key expressions were applied (IT-aided tools: 134, IT-integrated tools: 145) and led to 748 matches with tools of the BERUFENET tool catalog. Using these results in the occupations-tools matrix, we identified 2,402 occupations with (only) IT-aided tools, 370 occupations have IT-integrated tools,

[8] With regard to the basic sample of all workers employed in 2011 and 2016 (without any data selection), this is a share of approximately 40%.

[9] See https://berufenet.arbeitsagentur.de/

whereas only remaining 191 occupations do not have any digital tools within their portfolio. The relatively small number of occupations with IT-integrated tools might be explained by the circumstance that due to the editorial process of BERUFENET there is some time lag between the emergence of the real labor market demand and the inclusion in the database. Another reason might be that due to the flexibility of standard PC work places some new digital tools are included in those tool descriptions referring to 'PC work places' and consequently are not marked as separate tools (e.g. cloud computing services, machine learning algorithms).

Table 2: List of digital tools categories

Category	Code	Dictionary	Matches in BERUFENET	
		Keywords	Digitals tools in tools catalogue	Occupations with digital tools
01 IT-aided tools	cat1	134	594	2,402
02 IT-integrated tools	cat2	145	154	370
00 Total of 'Digital tools'	cat0	**279**	**748**	**2,772**

Note: Numbers of tools without matches in the digital tool catalog: 5,171; Number of occupations without any digital tool: 191.

Based on the digital tools identified, we create an occupations-tools-matrix that allocates the number of digital tools to every single occupation and group them by categories of IT-aided and IT-integrated tools. To use the total amount of both digital and non-digital tools as denominator, we expand the matrix by the total count of tools per single occupation. This matrix facilitates the calculation of the (unweighted) digital-tools index *dtox*. The *dtox* describes the proportion of digital tools categories in the total sum of tools of single occupation occ8d (8-digit level) in year *t*.

$$\boldsymbol{dtox_{c_{occ8d,t}}} = \frac{\sum \boldsymbol{dto_{c,occ8d,t}}}{\sum \boldsymbol{tools_{c,occ8d,t}}}$$

where

$\boldsymbol{dtox_{c_{occ8d,t}}}$	is the 'digital tools index' of single occupation *occ8d.*
$\sum \boldsymbol{dto}_{c,occ8d,t}$	is the number of digital tools (category *c*) of occupation *occ8d* in year *t*.
$\sum \boldsymbol{tools}_{occ8d,t}$	is the number of all tools of occupation *occ8d* in year *t*.
c	Categories of digital tools*:* *1. IT-aided digital tools* *2.IT-integrated digital tools* *0. Digital tools total (1+2)*
occ8d	8-digit level of KldB2010
t	available year (here: 2017)

Because administrative employment data is only available on higher aggregated levels, starting at the 5-digit level of the KldB2010, we have to aggregate *dtox* from the 8-digit level to the 5-digit level. For the development of $\boldsymbol{dtox}_{c(\mathbf{8}-\boldsymbol{digit})}$ to $\boldsymbol{dtox}_{c(\mathbf{5}-\boldsymbol{digit})}$, we use a procedure similar to Dengler et al. (2014) and Janser (2017). Like their approaches, we use aggregated employee data of the federal employment statistics to generate occupational weights. These weights $\boldsymbol{w}$ are based on the proportion of the number of employees of occupational type *occ5 (5-digit level of KldB2010)* in total number of employees working in the *d* digit-level of the occupational classification KldB2010. Formally this is

$$\boldsymbol{w}_{\boldsymbol{occ5tod,t}} = \frac{\boldsymbol{emp}_{\boldsymbol{occ5} \in \boldsymbol{d},\boldsymbol{t}}}{\sum \boldsymbol{emp}_{\boldsymbol{occ5} \in \boldsymbol{d},\boldsymbol{t}}}$$

In the next step, the products of weights and *dtox* are added and lead to the weighted *dtox*[11] which we merge to our project dataset. $\boldsymbol{dtox}_{\boldsymbol{c}_{\boldsymbol{occd,t}}} = \sum_{\boldsymbol{occ5} \in \boldsymbol{d}=\mathbf{1}}^{\boldsymbol{n}} \boldsymbol{w}_{\boldsymbol{occ5tod,t}} * \boldsymbol{dtox}_{\boldsymbol{c}_{\boldsymbol{occ5,t}}}$

The BERUFENET is also the initial source of the tasks index introduced by Dengler et al. (2014). We use this index to identify e.g. the share of routine- and non-routine jobs. The tasks index is described in Dengler et al. (2014).

Descriptive evidence

After having compiled information from different data sources[12], Table 3 now compares several characteristics between workers of digital pioneers, the digital peloton and digital latecomers. It can be seen that workers from pioneers are more qualified than workers from latecomers. Both, the occupational requirement level (more experts and specialists) as well as the formal qualification level (more high-skilled workers) is higher than for workers of latecomers. Regarding the gender distribution, the share of female workers is higher among pioneers. Employees in those firms are distinctly younger and more often employed with a fixed work contract. Considering the tasks and tools distribution this is in accordance with the observed qualification and requirement level. Pioneers employ more workers performing analytical and interactive tasks that work with computer-aided or computer-integrated work tools. On the contrary, pioneers have fewer employees performing manual tasks. This workforce composition might simply be driven by the characteristics of the employer: We observe that workers of pioneers are disproportionately often employed in firms of knowledge-intensive services sectors and ICT. Moreover, digital pioneer firms are larger and more often located in dense metropolitan areas and their surroundings. These differences in employer characteristics are also reflected in the mean wages of workers: workers of pioneers earn €122 per day, this is about 13 percent more than the wage of latecomers (€108). Controlling for these differences in observed characteristics between pioneer firms' workers and latecomers' workers in OLS- regressions, we observe that this wage premium decreases to 2 percent.[13] Note that the OLS-results suffer from unobserved heterogeneity between workers. In order to circumvent this

[11] A first impression of dtox at a more aggregated level (occupational segments) is given by Appendix Table A1. Moreover, Appendix Table A2 gives an overview of the digital-tools index for different requirements levels.

[12] Some more variables (for instance gross outputs) are gathered from the establishment panel of the IAB.

[13] The OLS wage level results are not contained in the paper, but available from the authors on request. It should be noted, however, that the estimated coefficient is statistically significantly different from 0 at 1 percent level indicating a robust wage premium for pioneer firms' workers compared with latecomer firms' workers.

problem and because we are interested in wage growth effects of digitalisation, we apply a model using differences in the next section.

Table 3: Sample means for workers in digital pioneer firms, digital peloton firms and digital latecomer firms

	Latecomers	Peloton	Pioneers
Share of workers by requirement level			
Unskilled/Semi-skilled worker	14.6	9.2	11.6
Skilled worker	56.6	58.0	51.7
Specialist	17.3	17.8	19.0
Expert	11.4	15.0	17.7
Share of workers by educational level			
Missings	0.3	0.4	0.3
Low-skilled	4.0	3.8	4.4
Skilled	79.0	74.4	72.5
High-skilled	16.7	21.4	22.8
Share of female workers	19.6	31.1	28.0
Mean age	44.8	45.1	44.2
Share of temporary workers	3.0	4.5	3.9
Share of foreign workers	4.6	4.7	4.8
Share of analytical tsasks	21.4	25.8	27.3
Share of interactive tasks	4.4	9.5	8.7
Share of routine cognitive tasks	32.5	31.3	32.7
Share of routine manual tasks	22.8	16.6	17.2
Share of non-routine manual tasks	19.0	16.9	14.1
Share of digital tools (total, $dtox_{\mathbf{total}}$)	28.5	31.4	33.9
Share of digital tools (IT-aided, $dtox_{IT\text{-}AID}$)	26.2	29.1	31.4
Share of digital tools (IT-integrated, $dtox_{IT\text{-}INT}$)	2.2	2.2	2.5
Share of workers by sector			
Non-knowledge intensive manufacturing	32.7	21.0	20.3
Knowledge intensive manufacturing	49.8	29.9	24.9
Non-knowledge intensive services	6.3	16.4	8.0
Knowledge intensive services	5.4	21.0	21.9
Information and communication technologies (ICT)	5.8	11.8	24.8
Share of workers by type of the region			
Dense metropolitan areas	17.9	34.3	25.6
Metropolitan surroundings	32.1	27.2	33.0
Central cities in rural areas	34.7	22.5	22.1
Rural areas	15.2	16.1	19.3
Daily wages (in €, imputed and deflated)	107.84	118.51	122.26
Mean establishment size	276.77	514.59	631.95
Number of workers	11,539	48,426	31,017
Number of establishments	280	862	383

Source: 'IAB-ZEW Labour Market 4.0' establishment survey, BeH, BERUFENET, IAB Establishment Panel, own calculations

3 Econometric analysis

3.1 Empirical approach

As described above, our analyses focus on full-time working males and females staying within their establishment during the observation period. The aim of the analyses is to estimate the effects of firms' investments in new digital technologies on wages of workers. We specifically investigate which groups of workers are positively or negatively affected by the digital transformation going on in recent years. Besides qualification, sex, age or sector affiliation, we deeply consider the role of tasks workers perform in their jobs and the role of work equipment (namely the degree of digital work tools in occupations) they use during their work.

To estimate the effects of investments in new digital technologies, we classify the establishment as shown above into 'pioneers' (these firms invest in new digital technologies between 2011 and 2016), 'peloton' firms (these firms invest in digital technologies to a small extent) and 'latecomers' (these firms do not invest in new digital technologies and also don't use them in 2016). This information is captured by dummy variables for the peloton and for pioneers which we include into Mincer-type wage growth regressions taking latecomers as reference group. We address time varying firm- and workers characteristics by including a battery of control variables, all time invariant characteristics are removed through differencing. Formally, the estimated model is

$$\boldsymbol{y_{ift} = \beta_0 + \beta_1 DPioneer_{ift} + \beta_2 DPeloton_{ift} + \beta_3 X_{ift} + \mu_i + \vartheta_f + \delta_t + \varepsilon_{ift}} \qquad (1)$$

$\boldsymbol{y_{ift}}$ denotes the log wage of individual i in firm f in year t. $\boldsymbol{X_{ift}}$ contains time-varying individual and firm-related (individual) characteristics like individual age, the digital tools index, the tasks index, (log) establishment size, establishments' gross outputs, and the shares of foreigners, female workers, highly educated workers, temporary workers etc. at the establishment level. All time constant individual characteristics like unobserved ability, ambition, and motivation are contained in $\boldsymbol{\mu_i}$. They are removed by our approach as well as the time constant firm characteristics $\boldsymbol{\vartheta_f}$ (like the location of the firm or sector affiliation). $\boldsymbol{\delta_t}$ captures general time shocks, and $\boldsymbol{\varepsilon_{ift}}$ represents erratic shocks. The effects of investments into new digital technologies at the establishment level are captured by the coefficient $\boldsymbol{\beta}$. $\boldsymbol{\beta_1}$ of the dummy variable $\boldsymbol{DPioneer_{ift}}$ and $\boldsymbol{\beta_2}$ of the dummy variable $\boldsymbol{DPeloton_{ift}}$ capture the effects for being employed in a pioneer or peloton firm relative to being employed in a latecomer firm.

We estimate this wage equation for the aggregate as well as for different sub-groups of workers (by sex, age, education, sector, main tasks groups, digital tools categories and by interactions of sector and education, sector and tasks etc.) The results of these estimates give us an idea which workers suffer or benefit from the digital transformation in terms of wages.

3.2 Estimation results

Table 4 shows the results of the individual fixed effects estimates. Column (1) contains the results for the sample of all workers. The wage growth effect of being in a digital pioneer firm instead of a latecomer firm is 0.7 percentage points between the years 2011 and 2016. This effect is moderate but positive and significantly different from zero at a 1 percent level. Hence, our result contradicts the literature that suggests negative wage effects of new technologies (for instance, Acemoglu and Restrepo, 2017) and supports those papers that suggest positive effects on wages (for instance, Graetz and Michaels, 2015). Note, however, that the mentioned studies investigate the effects of industrial robots on wages. In our view, this technology is not new. As a consequence, our results do neither directly support nor contradict the literature because - to our knowledge - our study is the first that analyzes the wage effects of new digital technologies like big data, cloud computing systems, internet platforms, cyber-physical / embedded systems or the internet of things. Moreover, our study focuses on a specific group of directly affected workers, i.e. establishment stayers. We do not investigate the effects of new digital technologies on employment in this paper[14], hence, possible selection effects could explain a part of the positive wage growth effects. This would be the case if pioneer firms lay off low-performance workers more often than latecomer firms. A glance into our selection process reveals, however, that the construction of our balanced panel of establishment stayers affects latecomers and pioneers in comparably the same manner: 67.3 percent of pioneer firm workers and 68.4 percent of latecomer firm workers survive this selection step. That could be understand as a hint that selection effects do not bias the presented results to a large amount. Digging deeper, we investigate which groups of workers predominantly are affected by our selection. Columns (1) and (2) of Table A3 show mean wages and observation numbers of different skill groups in latecomer, peloton and pioneer firms. For all 735 low-skilled latecomer workers the mean wage in 2011 is €81.78. The balancing of the sample decreases the number of workers to 475 workers (column (4)) and increases the mean wage by 6 percent to €86.82 (column 3). Here, the impact of the selection on wages and number of workers is a bit lower than in peloton and pioneer firms. For the other skill groups, however, the balancing has comparably the same effects.

[14] For the effects of new digital technologies on employment see Arntz et al. (2017).

Table 4: Results of the fixed-effects estimates for all workers and specific groups of workers (gender and skill groups)

Variable	All workers	Male workers	Female workers	Low-skilled workers	Skilled workers	High-skilled workers
Dummy indicator: Wage growth effect of peloton firms vs. latecomers	0.0059**	0.0055**	0.0067	0.0307***	0.0064***	-0.0032
Dummy indicator: Wage growth effect of pioneers vs. latecomers	**0.0072*** **	**0.0077*** **	**0.0061**	**0.0314*** **	**0.0099*** **	**-0.0104**
Establishment's share of digital tools ($dtox_{IT\text{-}AID}$)	0.0769*	0.1939***	-0.2252**	0.1223	-0.034	0.4034***
Establishment's share of digital tools ($dtox_{IT\text{-}INT}$)	-0.6436***	-0.6121***	-0.6598*	-1.0403	-0.4276*	-0.7316*
Establishment's share of analytical tasks	0.2190***	0.1774***	0.3169**	-0.1607	0.3144***	-0.0341
Establishment's share of interactive tasks	0.0241	-0.0523	0.094	-0.0541	0.1336*	-0.2807
Establishment's share of routine-cognitive tasks	-0.0187	-0.0263	-0.0324	0.0346	0.0327	-0.2285
Establishment's share of routine-manual tasks	0.1623***	0.2167***	-0.0579	0.0139	0.2191***	-0.0222
Establishment's share of female workers	-0.0088	0.0108	-0.0246	-0.0777	0.0138	-0.0331
Individual share of analytical tasks	0.0428*	0.0453*	0.046	0.3643***	0.0545*	-0.0986
Individual share of interactive tasks	0.0303	0.0242	0.0704	0.2405	0.0027	-0.0638
Individual share of routine-cognitive tasks	0.0171	0.0149	0.0358	0.1513	0.0155	-0.0779
Individual share of routine-manual tasks	-0.0283	-0.0399	0.0758	0.1670*	-0.024	-0.2323*
Individual share of digital tools ($dtox_{IT\text{-}AID}$)	0.0719***	0.0675***	0.0855*	-0.0776	0.0655***	0.1697*
Individual share of digital tools ($dtox_{IT\text{-}INT}$)	-0.0168	-0.117	0.3026	-0.1452	0.0872	-0.1499
Constant	6.1656***	6.2508***	6.0075***	7.2549***	5.8222***	8.5033***
Time dummy for the year 2016, individual age effects (squared; interaction effects with being in the highest age category) and further establishment controls (log size (linear + squared), mean age of workers, share of foreign workers, share of temporary workers, share of high-skilled workers, log gross output (lin. + squared)) are included						
N	180,473	129,086	51,387	7,546	134,444	38,483
R-squared	0.2885	0.3026	0.2660	0.3325	0.3480	0.1981
F	1182.71	950.08	336.80	64.58	1162.13	152.61

Notes: ***p<0.01, **p<0.05, *p<0.1
Source: 'IAB-ZEW Labour Market 4.0' establishment survey, BeH, BERUFENET, IAB Establishment Panel, own calculations.

Column (1) of Table 4 demonstrates that the wage growth effect is higher in peloton firms compared with latecomer firms. The effect amounts to 0.6 percentage points. Note that both effects – for peloton firms as well as for pioneer firms – are highly robust with regard to inclusion or exclusion of control variables (for instance, we additionally included controls for occupational changes on the individual as well as the firm level).

Results by sex, education and age: The remainder of Table 4 depicts the estimation results for specific worker groups. Columns (2) and (3) show that the wage growth effect of investments into new digital technologies is more pronounced for male workers than for female workers. For male workers it amounts to 0.8 percentage points and is statistically highly significant. For female workers it is 0.6 percentage points and statistically not different from zero. It should be noted that the sample size is distinctly larger

for men. Before we present our findings on the impact of digitization on wages, let us first summarize previous results of other studies. According to Akerman et al. (2015) the access to broadband internet improves (worsens) the labor market outcomes and productivity of skilled (unskilled) workers. Dauth et al. (2017) find a negative impact of robots on individual earnings arising mainly for medium-skilled workers in machine-operating occupations, while high-skilled managers gain. Interestingly, we find the largest positive effect for low-skilled workers (3.1 percentage points, see column (4)). For skilled workers it is 1 percentage point (see column (5)), for high-skilled workers it amounts to -1 percentage point, but is statistically not significant (see column (6)).[15] We interpret these results in such a way that it pays out for low-skilled and skilled establishment stayers when firms invest in new digital technologies.
For this analysis, however, we compare low-skilled stayers in pioneer firms with low-skilled stayers in latecomer firms and also skilled stayers in pioneer firms with skilled stayers in latecomer firms. Hence, it does not necessarily mean that low-skilled and skilled workers benefit more from investments into new digital technologies than their high-skilled colleagues within the firm.[16]

Regarding age effects, it can be seen from Table 5 that especially younger workers benefit from being employed in a pioneer firm compared to being employed in a latecomer firm. The wage growth effect amounts to 2.5 percentage points. For middle age and older workers the effect is 0.4 percentage points, only. Since accumulation of firm-specific and general human capital is especially important during the first years of the employment biography, this could be a hint that the accumulation of human capital benefits from the use of new technologies in firms.

[15] Similar results arise when differencing the workers by the requirement level of their jobs. The wage growth effect is most pronounced for workers in a job requiring an occupational qualification (1.5 percentage points). The growth effect for specialists and experts are negative but statistically not significantly different from zero at a 5 percent level. These results are not contained in the paper, but available from the authors on request.

[16] We take up this issue in a plausibility check presented below.

Table 5: Results of the fixed-effects estimates for different age groups of workers

Variable	Younger workers (<30 years in 2011)	Medium-aged workers (30-49 years in 2011)	Older workers (50 or older in 2011)
Dummy indicator: Wage growth effect of peloton firms vs. latecomers	0.0074	0.0048*	0.0072*
Dummy indicator: Wage growth effect of pioneers vs. latecomers	**0.0255*** **	**0.0043**	**0.0042**
Establishment's share of digital tools ($dtox_{IT\text{-}AID}$)	0.3590**	0.0859	-0.0922
Establishment's share of digital tools ($dtox_{IT\text{-}INT}$)	-0.4837	-0.7666***	-0.2873
Establishment's share of analytical tasks	-0.0031	0.2070***	0.3231***
Establishment's share of interactive tasks	-0.2276	0.0023	0.1979
Establishment's share of routine-cognitive tasks	-0.4790**	0.0064	0.1221
Establishment's share of routine-manual tasks	-0.0927	0.1564*	0.2734***
Establishment's share of female workers	0.0336	-0.0158	-0.0071
Individual share of analytical tasks	0.0021	0.0635*	0.0173
Individual share of interactive tasks	0.1241	0.0336	-0.0689
Individual share of routine-cognitive tasks	-0.0134	0.0201	0.0442
Individual share of routine-manual tasks	-0.0664	0.0017	-0.0617
Individual share of digital tools ($dtox_{IT\text{-}AID}$)	0.1178***	0.0737***	-0.0183
Individual share of digital tools ($dtox_{IT\text{-}INT}$)	-0.1356	-0.0085	0.0417
Constant	5.3267***	5.5569***	5.2672***
Time dummy, individual age effects (squared; interaction effects with being in the highest age category) and further establishment controls (log size (linear + squared, mean age of workers, share of foreign workers, share of temporary workers, share of high-skilled workers, log gross output (lin. + squared)) included			
N	24,224	108,882	47,367
R-squared	0.4907	0.2586	0.1346
F	492.20	641.66	152.57

Notes: ***p<0.01, **p<0.05, *p<0.1
Source: ‘IAB-ZEW Labour Market 4.0’ establishment survey, BeH, BERUFENET, IAB Establishment Panel, own calculations

Tools and tasks: To investigate this hypothesis more deeply, we categorize our sample by the information on the work equipment (tools) and tasks of occupations. As described above, we are able to differentiate between IT-aided tools ($dtox_{IT\text{-}AID}$), i.e. tools that are electronically based or supported, such as computers, printers, electronic machines, that are not explicitly dedicated to an industry 4.0 feature and IT-integrated tools ($dtox_{IT\text{-}INT}$), i.e. tools that are electronically based or supported and that are explicitly dedicated to an industry 4.0 or services 4.0 feature, such as 3D printers, machine learning software or mobile robots. We now assign the workforce to three categories using the $dtox_{IT\text{-}AID}$ – distribution in 2011. The average share of IT-aided work equipment is 29.4 percent on average in 2011. The median is somewhat lower at 25.6 percent. The category ‘low’ comprises workers with a below the median share of $dtox_{IT\text{-}AID}$. The category ‘middle’ comprises workers with $dtox_{IT\text{-}AID}$ –share between the median and the 75th percentile of the distribution (this is at 49.8 percent) and the category ‘high’ comprises workers with $dtox_{IT\text{-}AID}$ –share of 75th percentile or higher. The same categorization is done for $dtox_{IT\text{-}INT}$. Here, the median in 2011 is at 0.49 percent and p75 is at 3.5 percent. We see that new digital work tools are still barely used. As discussed above, this might be explained by the circumstance that due to the editorial process of BERUFENET there is some time lag between the emergence of the real labor market demand and the inclusion of new working tools in the database. The left panel of Table 6 presents the results for the three $\text{dtox}_{\text{IT-AID}}$- groups: It is at the first glance surprising that the wage growth effect is highest for individuals typically working with non-IT-aided tools (1.6 percentage points). The wage growth effect is even negative (but not significant) for workers with a high share of IT-aided tools. This corresponds with estimates for different tasks groups (here, workers are classified with regard to the main task of the worker's occupation) where wage growth effect is negative (but not significant) for workers with a high share of analytical and interactive tasks and statistically significant and positive for workers often performing routine cognitive tasks (see Appendix Table A4).

Before shedding light on these unexpected results, we turn to the three $\text{dtox}_{\text{IT-INT}}$ groups on the right panel of Table 6: Here, we see the largest wage growth effect for workers of the medium category (2 percentage points). Although the effect is not significant for the highest category, it is highly significant for the intermediate one. Hence, it seems that the usage of 4.0 work tools has some beneficial effect on the wage growth of workers.

Table 6: Results of fixed-effects estimates for tools groups

Variable	$\text{dtox}_{\text{IT-AID}}$ low	$\text{dtox}_{\text{IT-AID}}$ medium	$\text{dtox}_{\text{IT-AID}}$ high	$\text{dtox}_{\text{IT-INT}}$ low	$\text{dtox}_{\text{IT-INT}}$ medium	$\text{dtox}_{\text{IT-INT}}$ high
Dummy indicator: Wage growth effect of pelo-ton firms vs. latecomers	0.0127***	0.0023	-0.0061	0.0016	0.0224***	-0.0061
Dummy indicator: Wage growth effect of pi-oneers vs. latecomers	**0.0161*** **	**0.0028**	**-0.0076**	**0.003**	**0.0197*** **	**0.0007**
Establishment's share of digital tools ($\text{dtox}_{\text{IT-AID}}$)	-0.0869	0.0619	0.3548***	-0.079	0.2039**	0.1341*
Establishment's share of digital tools ($\text{dtox}_{\text{IT-INT}}$)	-1.0099***	-0.4599	-0.5103	-0.7146*	-0.8111**	-0.4019
Establishment's share of analytical tasks	0.2379***	0.1818	0.0648	0.2242**	0.3174**	0.0467
Establishment's share of interactive tasks	0.3327***	-0.0033	-0.2198	0.0691	0.0848	-0.1141
Establishment's share of routine-cognitive tasks	0.0425	-0.0015	-0.1179	0.0113	0.0425	-0.1353
Establishment's share of routine-manual tasks	0.1873***	0.1102	0.1309	0.1321	0.2069**	0.1319
Establishment's share of female workers	0.0447	-0.0591	-0.0375	0.0386	-0.043	-0.1050**
Individual share of analytical tasks	-0.0109	0.1036**	0.0276	0.0438	0.0005	0.0134
Individual share of interactive tasks	-0.067	0.0305	0.12	-0.0673	0.1136*	0.2183*
Individual share of routine-cognitive tasks	-0.0014	0.0344	0.0685	0.0288	0.0075	0.0453
Individual share of routine-manual tasks	-0.017	0.0172	-0.0079	0.0333	-0.0043	-0.0679
Individual share of digital tools ($\text{dtox}_{\text{IT-AID}}$)	0.1916***	0.0021	-0.0732*	0.1416***	0.1179***	-0.0376
Individual share of digital tools ($\text{dtox}_{\text{IT-INT}}$)	0.2472**	-0.1541	-0.0664	0.3735***	0.0064	-0.3945***
Constant	5.7021***	6.7020***	6.8037***	6.2429***	6.1374***	6.1058***
Time dummy. individual age effects (squared; interaction effects with being in the highest age category) and further establishment controls (log size (linear + squared. mean age of workers. share of foreign workers. share of temporary workers. share of female workers. share of high-skilled workers. log gross output (lin. + squared)) included						
N	90,176	41,597	48,700	80,620	54,919	44,934
R-squared	0.3498	0.2746	0.2389	0.2865	0.3007	0.2884
F	794.68	261.31	261.71	527.94	394.28	301.92

Notes: ***p<0.01. **p<0.05. *p<0.1

Source: 'IAB-ZEW Labour Market 4.0' establishment survey, BeH. BERUFENET, IAB Establishment Panel, own calculations

Sector-specific results: One could argue, that comparing e.g. workers primarily using non-digital working tools between latecomer firms and pioneer firms could be misleading when pioneer firms typically are (e.g.) large, modern IT-firms and latecomer firms typically are (e.g.) small construction firms. In the former, it would be quite unusual that workers primarily use non-digital working tools while this is entirely normal in the latter. Although having this battery of control variables included in the fixed effects approach, it would mean in the worst case comparing apples with oranges. Therefore we think that sector-specific estimates are better suited to understand the effects of new digital technology investments on wages. Table 7 shows that the wage growth effects for being in a pioneer firm vs. a latecomer firm is significantly positive in the sector aggregates knowledge intensive manufacturing (1.9 percentage points; e.g. car manufacturers or machine manufacturers) and non-knowledge intensive services (3.6 percentage points; e.g. wholesalers, logistics, restaurants).

Table 7: Results of the sector-specific fixed-effects estimates

Variable	non-knowledge intensive manufacturing	knowledge intensive manufacturing	non-knowledge intensive services	knowledge intensive services	ICT
Dummy indicator: Wage growth effect of peloton firms vs. latecomers	0.0079**	0.0009	0.0447***	-0.0108	0.0029
Dummy indicator: Wage growth effect of pioneers vs. latecomers	**-0.0029**	**0.0189*** **	**0.0361*** **	**-0.0087**	**0.0041**
Establishment's share of digital tools ($dtox_{IT\text{-}AID}$)	-0.1301	0.4012***	-0.2006	-0.0073	0.5172***
Establishment's share of digital tools ($dtox_{IT\text{-}INT}$)	-0.4325	-1.1079**	0.7896	-0.9176*	-0.2238
Establishment's share of analytical tasks	0.5394***	0.0662	0.1322	0.0894	-0.2506
Establishment's share of interactive tasks	-0.6195**	-0.7350***	0.1016	0.6917***	-0.7138***
Establishment's share of routine-cognitive tasks	0.2112	-0.3768***	-0.1872	-0.1032	-0.1847
Establishment's share of routine-manual tasks	0.0206	0.0765	0.1335	0.1307	0.0138
Establishment's share of female workers	0.0333	0.0724	0.0196	-0.0655	-0.0642
Individual share of analytical tasks	0.0701	0.1049**	0.0167	-0.0431	0.033
Individual share of interactive tasks	-0.0514	0.1995***	-0.1059	-0.1244	0.091
Individual share of routine-cognitive tasks	0.0256	0.0211	0.0619	-0.005	0.0259
Individual share of routine-manual tasks	-0.0332	0.0243	-0.1305	0.0351	0.0415
Individual share of digital tools ($dtox_{IT\text{-}AID}$)	0.1091*	0.0311	0.1239	0.1754**	0.0304
Individual share of digital tools ($dtox_{IT\text{-}INT}$)	0.0166	-0.154	0.1225	-0.0142	0.0686
Constant	5.3890***	6.1491***	6.3865***	6.2274***	6.9320***
Time dummy, individual age effects (squared; interaction effects with being in the highest age category) and further establishment controls (log size (linear + squared, mean age of workers, share of foreign workers, share of temporary workers, share of high-skilled workers, log gross output (lin. + squared)) included					
N	40,358	55,121	22,274	34,614	28,106
R-squared	0.3376	0.2981	0.3341	0.2566	0.2734
F	321.05	422.50	212.06	202.75	189.53

Notes: ***p<0.01, **p<0.05, *p<0.1

Source: 'IAB-ZEW Labour Market 4.0' establishment survey, BeH, BERUFENET, IAB Establishment Panel, own calculations

Digging deeper, Table 8 shows the estimated coefficients of the treatment variable[17] for the different skill groups within these sector aggregates. In both knowledge intensive manufacturing and non-knowledge intensive services the wage growth effect is most pronounced for low-skilled and skilled workers, and not significant for high-skilled workers. This points to the fact that the positive effect detected for both sectors is actually driven by the effects for low-skilled and skilled persons. Also in knowledge intensive services (e.g. scientific services, banks, insurances) we observe large positive wage growth effects especially for low-skilled workers. Here, the effect for high-skilled workers is negative (-5 percentage points) and statistically significant at the 1 percent level.

Table 8: Estimated coefficients for dummy indicator 'wage growth effect of pioneers vs. latecomers' for education groups by sectors

	skill level	Wage growth effect of pioneers vs. latecomers
Non-knowledge intensive manufacturing	low	0.0164
	medium	-0.0009
	high	-0.0164
Knowledge intensive manufacturing	low	0.0367*
	medium	0.0173***
	high	0.011
Non-knowledge intensive services	low	0.0785*
	medium	0.0414***
	high	-0.0162
Knowledge intensive services	low	0.1490*
	medium	0.0209**
	high	-0.0524***
ICT	low	-0.0399
	medium	0.0101
	high	-0.0126

Notes: ***p<0.01, **p<0.05, *p<0.1
Source: 'IAB-ZEW Labour Market 4.0' establishment survey, BeH, BERUFENET, IAB Establishment Panel, own calculations.

Repeating the $dtox_{IT\text{-}INT}$ groups analyses separated by sectors (see Table 9), we observe significant effects only for the intermediate IT-aided tools tools category in knowledge-intensive manufacturing and the highest category in knowledge-intensive services. Our interpretation is, that the usage of these new digital working tools adds to explain the higher wage growth of pioneer firms' workers within both sectors. Apparently, the usage of these new digital work tools is not restricted to the high-skilled workers within these establishments. A further positive effect in both sectors is detected for workers who do not use IT-aided working tools (by repeating the $dtox_{IT\text{-}AID}$ - groups analyses separated for sectors[18]). In terms of wages, it seems that the usage of work-equipment is polarized in a sense that people using non-digitalized and high-digitalized work equipment benefit from the firms' digital transformation while this is not

[17] For sake of the reader´s convenience we show only the estimated coefficients of the treatment variable and not the complete results tables. Of course, all tables are available from the authors on request.

[18] The results of this analysis are not documented in the paper, but are available from the authors on request.

the case for workers using equipment with an intermediate share of digitalisation. In order to recheck this finding we change our point of view and focus on the employees in pioneer firms.

Table 9: Estimated coefficients for dummy indicator'wage growth effect of pioneers vs. latecomers' for dtox$_{IT\text{-}INT}$ groups by sectors

	dtox$_{IT\text{-}INT}$	Wage growth effect of pioneers vs. latecomers
Non-knowledge intensive manufacturing	low	-0,0044
	medium	0,0115
	high	-0,0086
Knowledge intensive manufacturing	low	0,0082
	medium	0.0386***
	high	0,0056
Non-knowledge intensive services	low	-0,003
	medium	0,0284
	high	0.0719***
Knowledge intensive services	low	-0,0013
	medium	-0,039
	high	0,0044
ICT	low	0,0044
	medium	-0,002
	high	-0,0014

Notes: ***p<0.01, **p<0.05, *p<0.1
Source: 'IAB-ZEW Labour Market 4.0' establishment survey, BeH, BERUFENET, IAB Establishment Panel, own calculations.

Who benefits within pioneer firms?

To measure wage growth effects for workers within pioneer firms we interact the dummy variable which indicates the affiliation to a specific group (for instance skilled or high-skilled) with the year dummy for 2016.[19] Starting with differences between skill groups, it is worth noting that all effects are insignificant (without one exception: a positive effect of 1.5 percentage points for skilled workers relative to low-skilled workers in non-knowledge intensive manufacturing firms). That means that low-skilled, skilled and high-skilled workers within pioneer firms have comparably the same wage growth over the observation period. The above documented positive effect for low-skilled and skilled workers relative to the latecomer reference group is therefore less attributed to differing effects for skill groups within pioneer firms, but more attributed to differing wage growth rates in firms without new digital technology investments (looking into latecomer firms, we can actually observe that the wage growth rates increase with the skill level of the employees).

Turning to the work tools again, we observe a significant positive effect for workers in pioneer firms operating with IT-integrated tools (both for the intermediate and the highest category). Sector-specific analyses reveal, however, that these effects are most pronounced in ICT establishments. This might reflect the prominent role of the ICT sector as key enabler of the digital transformation. In this sector

[19] The results of this analysis are not documented in the paper, but are available from the authors on request.

digital tools are the most crucial - and often solely applied - tools for value generation. Due to this IT-centeredness, every worker (also intermediate and high-skilled workers) in the IT-focused value chain profit from investments in digital technologies.

4 Conclusions

The digital transformation being observed in the last years has led to an intense debate about its actual and possible future societal impacts. Due to lack of data, however, little is yet known on the actual extend of diffusion as well as corresponding effects of technological upgrading at the firm level on the wages of workers being employed in these firms.

To fill this gap, this paper uses a novel linked employer-employee data set that contains detailed information on firms' technological upgrading between 2011 and 2016, a recent period of rapid technological progress. Moreover, by introducing a digital tools index based on the German expert database BERUFENET it contains detailed information on the work equipment that is typically used by the workers. Hence, we observe the degree of digitalisation at both sides, the firm and the worker level. The data allow us to investigate the impact of technology investments on the remuneration of the employees within these firms.

We use the data to categorize the firms into three categories: 'digital pioneer' firms, the 'digital peloton' of establishments that have already invested in new digital technologies to a limited extent and latecomer firms that have not been investing in such technologies during our observation period from 2011 to 2016. We estimate individual fixed effects regression for the aggregate of workers as well as for different sub-group of workers (by sex, age, education, sector, main tasks groups, digital tools categories and by interactions of sector and education, sector and tasks etc.) and include the firm categories as dummy variables in the wage regression to identify the effect of firm's digital transformation on the effect of wages on the employed workers. In order to obtain valid results, we focus on the group of full-time employed establishment stayers. As a consequence, the paper remains silent about wage effects for firm leavers and firms' new entrants, and also about wage effects for part-time workers. The results of our estimates, however, give us an idea which workers suffer or benefit from the digital transformation in terms of wages.

For the aggregate, the wage growth effect of being in a digital technology pioneer firm instead of a latecomer firm is 0.7 percentage points between the years 2011 and 2016. This effect is moderate but positive and significantly different from zero. Hence, our result suggests positive effects of investments in new digital technology on wages. The estimates for different sub groups indicate that digitalisation especially pays out for younger workers, for low-skilled and for skilled workers when firms invest in new digital technologies. Our results show that the positive effects for low-skilled and skilled workers relative to the latecomer reference group is less attributed to differing effects for skill groups within pioneer firms, but more attributed to differing wage growth rates in firms without new digital technology investments. Looking into latecomer firms, we observe that the wage growth rates increase with the skill level of the employees while this is not the case within pioneer firms. In our opinion, these results indicate that workers, who are often perceived as the losers of the digital transformation (mostly in terms of employment) might nevertheless benefit in terms of wages.

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Appendix

Tables (Appendix)

Table A1: Occupational segments sorted by $dtox_{total}$ value (Kldb2010, 8-digit level)

KldB 2010	Occupational segment	$dtox_{total}$	$dtox_{IT\text{-}AID}$	$dtox_{IT\text{-}INT}$
S33	Business related service occupations	**0.517**	0.510	0.007
S31	Occupations in commerce and trade	**0.491**	0.454	0.037
S32	Occupations in business management and organisation	**0.485**	0.485	0.000
S41	Service occupations in the IT-sector and the natural sciences	**0.402**	0.369	0.033
S23	Service occupations in social sector and cultural work	**0.326**	0.317	0.009
S51	Safety and security occupations	**0.286**	0.286	0.001
S13	Occupations concerned with production technology	**0.248**	0.240	0.007
S52	Occupations in traffic and logistics	**0.246**	0.208	0.038
S22	Medical and non-medical health care occupations	**0.211**	0.169	0.042
S12	Manufacturing occupations	**0.210**	0.199	0.011
S21	Occupations in the food industry. in gastronomy and in tourism	**0.140**	0.140	0.000
S53	Occupations in cleaning services	**0.121**	0.119	0.002
S14	Occupations in building and interior construction	**0.101**	0.087	0.014
S11	Occupations in agriculture. forestry and horticulture	**0.093**	0.078	0.016

Notes: The table presents the ranking of occupational main groups with the highest $dtox_{total}$ values. The first value of column $dtox_{total}$ shows that 51.7 percent of tools in business related service occupations are digital tools. This values adds up from the two following columns: about 51.0 percent are IT-aided tools ($dtox_{IT\text{-}AID}$) and 0.7 percent are IT-integrated tools ($dtox_{IT\text{-}INT}$). The different values show that currently the share of IT-aided tools is dominant whereas the share of IT-integrated tools is relatively low (the highest value is 4.2 percent). This may reflect either the time lag of the editorial process and/or a weakness of current vocational training plans and other training concepts that do not cover those tools yet.
Source: BERUFENET 2017. own calculations.

Table A2: Digital-tools index *dtox* aggregated by requirement levels (weighted)

KldB 2010 5th digit	Requirement level	$dtox_{total}$	$dtox_{IT\text{-}AID}$	$dtox_{IT\text{-}INT}$
1	Unskilled/Semi-skilled worker	0.110	0.096	0.014
2	Skilled worker	0.293	0.278	0.015
3	Specialist	0.475	0.452	0.023
4	Expert	0.489	0.468	0.021

Notes: With a dtoxtotal of 0.489 the requirement level of experts (with mainly complex tasks) shows the highest values. Whereas the group of unskilled/semi-skilled workers has the lowest value (0.110). The distribution of dtoxIT-AID follows this pattern. whereas the distribution of IT-integrated tools is not that polarized yet (dtoxIT-INT Max: 0.023 (3 Specialist) / Min: 0.014 (1 Unskilled/Semi-skilled workers)).
Source: BERUFENET 2017, own calculations.

Table A3: The impact of balancing the panel 2011 on wages and observation numbers

		Unbalanced panel		Balanced panel		Differences (in percent)	
Firms	Skill group	Mean wage (in €)	N	Mean wage (in €)	N	Mean wage	Number of workers
Latecomer	1 low	81.78	735	86.82	475	6.2	-35.4
Peloton	1 low	84.95	3,413	92.91	1,920	9.4	-43.7
Pioneer	1 low	85.31	2,322	91.58	1,398	7.3	-39.8
Latecomer	2 med	89.35	13,586	93.65	9,132	4.8	-32.8
Peloton	2 med	94.00	59,963	100.53	36,131	7.0	-39.7
Pioneer	2 med	97.78	35,114	102.67	22,535	5.0	-35.8
Latecomer	3 high	143.97	3,255	150.97	1,932	4.9	-40.6
Peloton	3 high	149.67	19,685	158.55	10,375	5.9	-47.3
Pioneer	3 high	154.79	12,885	162.22	7,084	4.8	-45.0

Source: 'IAB-ZEW Labour Market 4.0' establishment survey, BeH, BERUFENET, IAB Establishment Panel, own calculations.

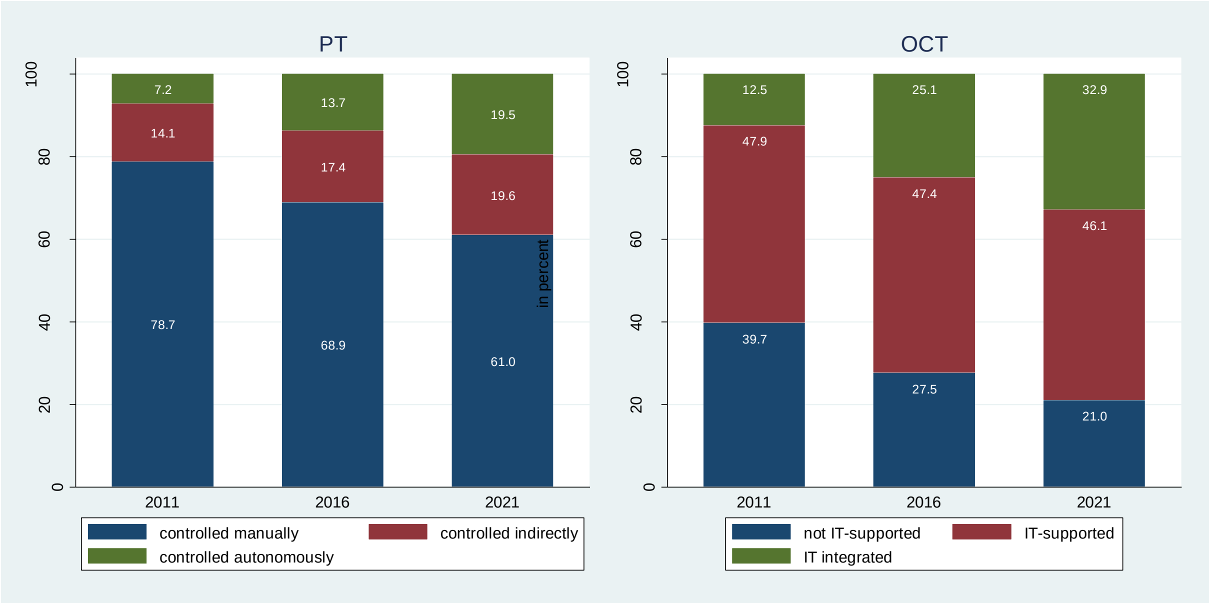
Table A4: Estimated coefficients for dummy indicator 'wage growth effect of pioneers vs. latecomers' for occupational tasks groups

Variable	main task: analytical	main task: interactive	main task: routine-cognitive	main task: routine-manual	main task: non-routine manual
Dummy indicator: Wage growth effect of pioneers vs. latecomers	-0.0074	-0.0175	0.0247***	0.0012	0.0115*

Source: 'IAB-ZEW Labour Market 4.0' establishment survey, BeH, BERUFENET, IAB Establishment Panel, own calculations.

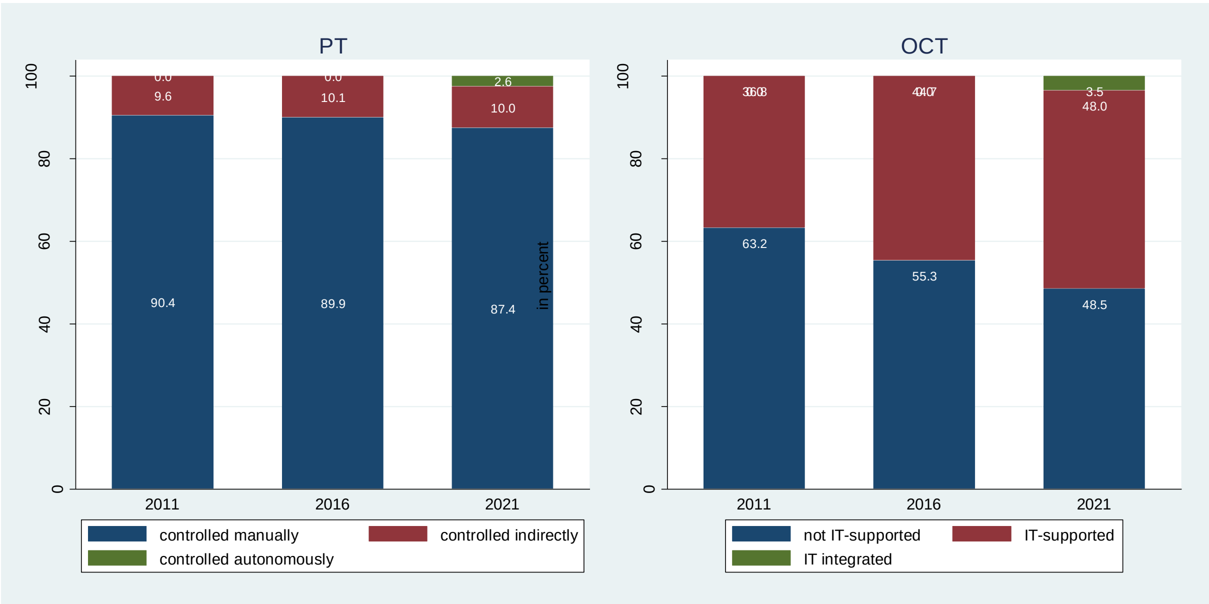
Figures (Appendix)

Figure A1: Trends in automation level of firms' work equipment for digital technology pioneers



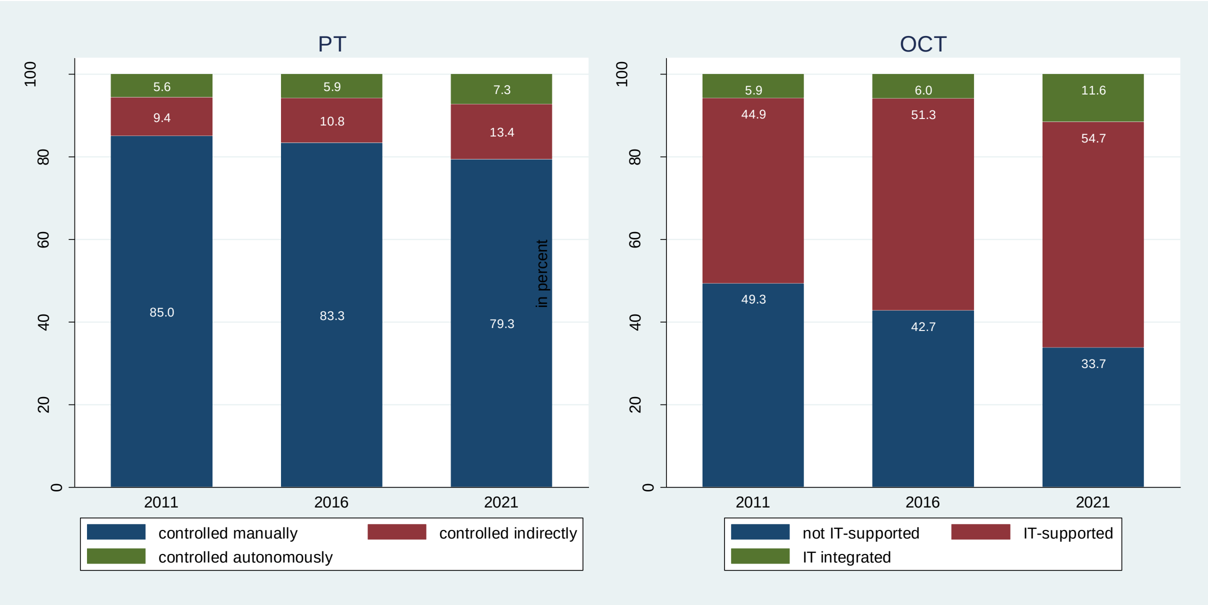
Source: 'IAB-ZEW Labour Market 4.0' establishment survey, own calculations.

Figure A2: Trends in automation level of firms' work equipment for latecomers



Source: 'IAB-ZEW Labour Market 4.0' establishment survey, own calculations.

Figure A3: Trends in automation level of firms' work equipment for the 'peloton'



Source: 'IAB-ZEW Labour Market 4.0' establishment survey, own calculations.