Original Article

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

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Abstract: The strong rise of digitalization, automation, machine learning and other related new digital technologies has led to an intense debate about their societal impacts. The transitions of occupations and the effects on labor demand and workers' wages are still open questions. Research projects dealing with this issue often face 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 establishments' technological upgrading between 2011 and 2016, a recent period of rapid technological progress. Furthermore, we are the first to develop 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 workers. Hence, we observe the degree of digitalization on both the establishment level and the worker level. The data allow us to investigate the impact of technology investments on the wage growth of employees within establishments. Overall, the results from individual level fixed effects estimates suggest that investments in new digital technologies at the establishment level positively affect the wages of the establishments' workers. Sector-specific results show that investments in new digital technologies increase wages in knowledge intensive production establishments and non-knowledge intensive services. The wage growth effects of employees in *digital pioneer* establishments relative to the specific reference group of workers in *digital latecomer* establishments are most pronounced for low- and medium-skilled workers.

Keywords: digital technologies, automation, digital tools, wage growth

JEL Classification: J31, J23, J24, O33

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1 Introduction

In recent years, advances in mobile robotics and machine learning have fostered the ongoing digitization¹ and automation in developed economies. Related innovations are characterized by a high degree of complexity, as they are capable of connecting humans and machines automatically and wirelessly. Two additional differences to former technological developments are the tremendous pace of new digital innovations and the wide-ranging effects on the whole economy and society. New digital technologies increasingly undertake tasks that were performed by human beings in the past (Brynjolfsson/McAfee 2014). This change in tasks conducted by employees has raised concerns that human employment will be increasingly replaced by computers, algorithms or robots. An increasing number of studies address, therefore, the labor market consequences of modern automation technologies. Frey and Osborne (2017) estimate that 47% of US employment is threatened by computer controlled smart machines. Although this anxiety appears exaggerated (see, for instance, Autor 2015; Arntz et al. 2017; Dengler/Matthes 2015), the net employment and wage effects of digitalization vary greatly depending on the measurement of the technologies used for the empirical estimation. As existing literature is confronted with a lack of data on the usage of new digital technologies, studies often exploit the change in occupational tasks resulting from the implementation of industrial robots (see, for instance, Acemoglu/Restrepo 2017; Dauth et al. 2017; Graetz/Michaels 2015).

In this paper, we apply a direct measure for the usage of new digital technologies to capture the labor market effects of digitalization and automation. First, we use a novel linked employer–employee data set that was developed by linking the “IAB-ZEW Labour Market 4.0” establishment survey with administrative German labor market data provided by the Institute for Employment Research (IAB) at the German Federal Employment Agency. This allows us to observe detailed information on the upgrading of new digital technologies by establishments between 2011 and 2016. Second, we use a digital tools index derived from text mining of the German occupational database, BERUFENET. This novel index contains detailed information on the degree of digitalization of the work equipment that is used by employees. Hence, we are

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

able to measure digitalization at both the establishment level and the worker level. The data allow us to investigate the impact of technology investments on the development of wages within establishments.

In past decades, a large strand of the literature—namely, the task-based approach—has addressed the concerns regarding the future development of employment and wages given that information and communication technologies, such as computers, are able to conduct tasks that have previously been performed by human workers.² The research has shown that computerization mostly affects repetitive, routine tasks that are mainly performed by medium-skilled occupations (Autor et al. 2003; Autor 2013). These tasks are replaced with technology, while non-routine cognitive tasks predominantly used in high-skilled occupations are complemented by computerization (see, for instance, Acemoglu/Autor 2011). This means that employment in occupations at the bottom and the top of the skill distribution increases more than in medium-skilled occupations. This employment polarization has been detected for many industrialized countries in the last two decades (Goos et al. 2014; Michaels et al. 2014; Goos et al. 2009). Several empirical studies have shown that this phenomenon occurs with a simultaneous polarization in the wage distribution, i.e. wages at both ends of the occupational skill distribution increase to a larger extent than those of medium-skilled workers (Autor/Dorn 2013; Dustmann et al. 2009; Autor et al. 2006; Acemoglu 2002). This literature predicts that especially medium-skilled workers are disadvantaged in terms of employability and wage growth due to investments in information and communication technologies, such as computers, which use electronics for the basic automatization of the production process.

Surprisingly, very little is known about the resulting labor market effects of cutting-edge digital technologies. Very recently, it has been suggested that the ongoing digitization might affect the jobs of high-skilled workers as much as the jobs of skilled or low-skilled workers (Frey/Osborne 2017; Pratt 2015). However, this hypothesis has not yet been proven by the empirical literature. The principal reason for this gap in the literature is a lack of data on the usage of new digital technologies, such as analytical tools for analyzing big data, cloud computing systems, internet platforms, cyber-physical/embedded systems or the internet of things. The existing literature only discusses the effects of the diffusion of industrial robots on the employment and wages of workers. For instance,

² By contrast, there are 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/Hitt 2000) and industries (see Stiroh 2002; Acemoglu et al. 2014).

Acemoglu and Restrepo (2017) find a negative effect of the diffusion of robots on employment and wages at the regional level. Their empirical specification focuses on the geographic variations in robot exposure within the US. They use the aggregated exposure to robots, which is measured by robots per thousand workers, for local labor markets, which are measured by 722 commuting zones. Graetz and Michaels (2015) find no significant reduction in the overall employment, while their estimates suggest that industrial robots may be reducing the employment of low-skilled workers. Furthermore, they find a positive effect of the diffusion of robots on wages. Their empirical specification focuses on the variations in robot usage across industries for 17 developed countries. Dauth et al. (2017) find that the diffusion of robots decreases employment in the manufacturing sector in Germany. They find that this decrease is fully offset by an increase in service jobs. In terms of wage development, they detect a negative impact of robots on individual earnings arising mainly for medium-skilled workers in machine-operating occupations, while the earnings of high-skilled managers increase. However, the approximation of digitalization through stationary industrial robots might be insufficient since they are predominantly applied in the production industry while digitization is of equal importance for the service industry. Hence, previous studies tend to underestimate the impact of automation and digitization technologies on the labor market. Furthermore, it remains questionable if industrial robots can be referred as “new digital technologies” since industrial robots are actually not new but have been used for several decades.

A prominent study that does not focus on industrial robots to measure new technologies 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. By relying on a direct measure of cutting-edge digital technologies at an establishment level for both the manufacturing and service sectors, we contribute to this literature strand a new and more precise measurement of digitalization. One of the first studies to directly investigate the impact of new digital technologies on employment is Arntz et al. (2018a). They use the direct measure of technological adoption obtained from the same novel linked employer–employee data used in our study to explore the job creation and job destruction channels at the establishment level. The results suggest positive employment effects from investments in new digital technologies. We build on this study and contribute individual level wage effects of investments into new digital technologies.

Our study is the first that focuses on digital technologies and uses administrative labor market data at the individual level to measure the labor market impact of digitalization. The results from individual level fixed effects estimates

suggest that establishments' investments in new digital technologies do not diminish the wage growth of the workforce. For workers employed in non-knowledge intensive services and knowledge intensive production establishments, investments in new digital technologies are associated with increasing wages. We also find heterogeneous effects across skill groups. The wage growth effects are most pronounced for low- and medium-skilled employees in *digital pioneer* establishments relative to the specific reference group of workers in *digital latecomer* establishments.

The remainder of the paper is organized as follows: the next section addresses 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 descriptive statistics

2.1 Data and sample selection

For our empirical analyses, we use a novel data set that 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.³ Approximately 2,000 establishments participated in the survey in 2016. The sample was drawn from the establishment data file of the IAB. It was stratified by four establishment size categories, East and West Germany and five sector categories differentiating between 1. non-knowledge intensive manufacturing (e. g. furniture producers, building establishments), 2. knowledge intensive manufacturing (e. g. car manufacturers, machine manufacturers), 3. non-knowledge intensive services (e. g. wholesalers, restaurants, logistics), 4. knowledge intensive services (e. g. scientific services, banks, insurances) and 5. information and communication technologies (ICT) (e. g. producers of data processing equipment, consumer electronics or telecommunications equipment, enterprises that provide services in information

³ Due to data protection requirements, these new data are not yet available to the scientific community. However, a scientific use file (SUF) will be provided by the Research Data Center (FDZ) of the German Federal Employment Agency at the IAB (see <http://fdz.iab.de>).

technology, telecommunication or data processing). While the basic differentiation is between producers and service establishments, the ICT sector (where both producers and service establishments are included) is viewed separately because of its central role as a technology hub and core enabler of 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 three different classes (see Table 1). The higher the class is, the higher the degree of digitization.

Table 1: Categorization of digital technology classes.

Digital Technology 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, copiers, fax machines.
2	PT 2: controlled indirectly/partly by human beings , e. g. CNC-machines, industrial robots.	OCT 2: IT-supported , e. g. computers, terminals, electronic cash registers or CAD-systems.
3	PT 3: controlled autonomously by machines , e. g. modern production systems like smart factories, cyber-physical/embedded systems and internet of things. Both PT 3 and OCT 3 comprise machines/computers that operate mostly (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.

Note: Categorization of production and office and communication technologies into three digital technology classes. The increasing number is associated with a higher degree of digitization/automation of the technology.

Source: “IAB-ZEW Labour Market 4.0” establishment survey.

PT 3 represents new digital production technologies (in Germany also called “industry 4.0 technology”) and OCT 3 represents new digital office and communication technologies (in Germany also called “services 4.0 technology”). In 2016, the establishments were asked for their current status as well as for the status five years ago and the expected status in the future (in five years). Collating this status 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 establishments only use OCT.

Figure 1 shows that the share of new digital technologies (both industry 4.0- and services 4.0-technologies) is still very limited. Looking at the values from 2016 (in the middle columns), an average of 5.1 % of PT and 7.8 % of OCT can be assigned to new digital technologies. The degree of IT-supported OCT (49.4 %) is also distinctly higher than the share of indirectly controlled PT (11.9 %). Due to the “natural” high volume of digital technologies in OCT, the share of non-IT-supported technologies is much lower (42.8 %) than the corresponding group of manually controlled PT (83.1 %). In both PT and OCT, there is a slight trend towards IT-supported and indirectly controlled technologies, but this trend seems to evolve rather slowly.

Figure 1: Trends in the usage of digital technologies across German establishments.
Note: Automation level of the establishments’ work equipment between 2011 and 2021, separated for production technologies (PT) and office and communication technologies (OCT).
Source: “IAB-ZEW Labour Market 4.0” establishment survey, own calculations.

Based on this categorization and further information provided by the survey,⁴ we differentiate the groups of establishments as follows: *Latecomers* are defined as establishments who indicate that they do not use new digital technologies; accordingly, the share of new digital technologies in the year 2016 is 0 % (see

⁴ Besides the categorization of PT and OCT, the manager/production managers of the establishment were generally asked whether “the usage of new digital technologies is a topic in the establishment”. 31 % answered “no, we haven’t yet considered the usage of new digital technologies”, 15 % answered “we don’t use these technologies at the moment, but we already deal with the topic”, 2 % said “we don’t use these technologies at the moment, but we already plan an investment”, 34 % said “we already use these technologies” and 18 % answered “the usage of these technologies is an essential part of our business” (see also Arntz et al. 2016).

Figure 2). *Pioneer* establishments in digital technologies (*pioneers*) already use new digital technologies and invested in new digital technologies between 2011 and 2016. For this group of establishments, the degree of IT-supported OCT increased from 12.5 % in 2011 to 25.1 % in the year 2016, and the degree of autonomously controlled PT increased from 7.2 % in 2011 to 13.7 % in 2016 (see Figure 4). The remaining establishments are gathered in the *peloton* group. The average degree of 4.0-technologies in the year 2016 is approximately 6 % for both OCT and PT (see Figure 3). This differentiation leads to 363 *latecomers* (18 % of the establishments in the sample), 1,172 *peloton* establishments (58 %) and 497 *pioneers* (25 %) in our data set.

Figure 2: Trends in the usage of digital technologies across latecomer establishments.

Note: Automation level of the establishments' work equipment between 2011 and 2021, separated for production technologies (PT) and office and communication technologies (OCT).

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

Employment histories: Next, we link the survey data to employment biographies from the social security records (*Beschäftigten-Historik*, BeH, Version 10.02.01-171117) of all workers employed in the surveyed establishments between 2011 and 2016. The BeH covers the majority of the German workforce and is representative of dependent workers.⁵ It contains important personal characteristics (sex, age, skill, nationality, job status, occupation) as well as information

⁵ 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.

Figure 3: Trends in the usage of digital technologies across peloton establishments.
Note: Automation level of the establishments’ work equipment between 2011 and 2021, separated for production technologies (PT) and office and communication technologies (OCT).
Source: “IAB-ZEW Labour Market 4.0” establishment survey, own calculations.

Figure 4: Trends in the usage of digital technologies across pioneer establishments.
Note: Automation level of the establishments’ work equipment between 2011 and 2021, separated for production technologies (PT) and office and communication technologies (OCT).
Source: “IAB-ZEW Labour Market 4.0” establishment survey, own calculations.

on the region, industry, and wage. Because the BeH is derived from mandatory employer notifications to the German social security system, the data are highly accurate and reliable.

Despite these strengths, the BeH suffers from some moderate limitations, as follows: first, earnings are top-coded in the data. For this reason, we estimate censored regressions for each year (we use age, skill, establishment size, occupation, establishments' foreigner share, region and type of region as covariates), separated for male and female workers, and impute the censored wages. We follow the procedure described in Dustmann et al. (2009), but we include more covariates than they do in their baseline imputation model. The wages are then deflated to 2010 prices. Second, working time is only reported in three categories: full-time, part-time with at least 50 % of full-time working hours and part-time with less than 50 % of full-time working hours. To avoid bias due to imprecise information on working time, we restrict our analysis to men and women (16–65 years-old) working full-time, excluding apprentices, trainees and working students. Third, the data show some inconsistencies (or missing data) with regard to workers' formal education, which we refer to in the following as "skill". 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 preceding or subsequent spells of the individuals' employment history. Finally, we exclude observations with dubious wage information below a specific time-varying threshold.⁶ Focusing on employment spells overlapping June 30th of a year, our sample selection comprises approximately 1.1 million worker-year observations.

The aim of our study is to investigate how workers' wages are affected by the investments in new digital technologies by establishments. 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 that are 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 does not discuss the wage effects for establishment leavers and new entrants to establishments (or the wage effects for part-time workers). We are aware that our sample might be a positive selection of workers. We discuss this issue in the last paragraph of Section 3. Altogether, we observe in each year 90,982 male and female full-time workers in 1,525 establishments.⁷

⁶ 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 % of the observations are dropped when applying this threshold.

⁷ 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 %.

BERUFENET: The data source from which we identify digital tools is the BERUFENET, an online expert database of the Federal Employment Agency.⁸ The BERUFENET offers detailed information about every single occupation, e. g. 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 purpose of this paper is the section on work items/tools (*Arbeitsgegenstaende*). We use a unique BERUFENET data extract of the Federal employment agency. This extract facilitates analyses of tools for 2,963 occupations at 8-digit level of KldB2010.

The definition of tools in BERUFENET is very broad and covers approximately fourteen thousand tools. After selecting suitable tools (tools in the narrow sense, e. g. no documents, no production output/finished products), we use 5,919 of them. We also test a version with the full set of available work equipment for robustness checks.⁹ However, the narrow set of work tools applied for the digital-tools index (*dtox*) presented in the remaining of this paper is the better choice to answer the research questions of this paper because it focuses only on those tools that are closely connected to the tasks performed. Another approach might be to count the digital tools as an absolute number and to rank the occupations in order of these numbers. Unfortunately, the documented tools differ widely between each individual occupation at BERUFENET. Hence, an occupation with many tools may also have many more digital tools than an occupation with less tools documented in BERUFENET. To avoid this “large-number-of-tools”-bias, we decided to apply the percentage of digital tools of the total number of tools.

Due to technical reasons, the tools data extract from BERUFENET is only available for 2016 so far (date of extract: June 13, 2016). Nevertheless, this cross-section data at the current edge facilitates calculating the share of digital tools

⁸ See <https://berufenet.arbeitsagentur.de/>. Each tool that is potentially relevant for an occupation undergoes an editorial selection process of the BERUFENET editorial team. If a tool is of minor relevance for an occupation, it is not included in the database or is not linked to the specific occupation, respectively. Hence, the digital tools index considers the importance of tools in the sense that it focuses only on core tools. Furthermore, we consider only selected groups of tools (e. g. groups “Machinery and devices” or “Utilities, packing materials and accessories”) and ignore less relevant groups (e. g. group “Documents”). However, the BERUFENET does not include information about the actual usage time of the tools and there is also no ranking of priorities between the tools listed in the section “Work items/tools” at BERUFENET.

⁹ These results are available on request from the authors.

—and even to differentiate between IT-aided (industry 2.0/3.0) and IT-integrated digital tools (industry 4.0) in 2016. However, because of the lack of data, we cannot state if this share has changed between 2011 and 2016. Therefore, the access to further years of tool data from BERUFENET is an important and promising target for future research.¹⁰

We divide the tools into three categories, as follows:

1. **IT-aided tools** are electronically based tools, such as computers, printers, and electronic machines (digital technology classes 1 and 2, see Table 1).
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 (digital technology class 3, see Table 1).
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, the identification of digital tools is based on a text mining procedure to identify digital tools. Adapting the text mining approach introduced by Janser (2018), we apply 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), which 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 that have IT-integrated tools, whereas only remaining 191 occupations

¹⁰ A potential alternative data source for tool information might be the BIBB/BAuA Employment Survey (e. g. 2012), which includes three questions related to tools: “What is the most important equipment in your work as ... ?”(F300), “How often does this job task occur in your work (often/sometimes/never): ...Working with computers? (F318); ...Using the internet or editing e-mails? (F319)” and “Have new computer programs been introduced in your immediate working environment in the last two years? (Yes/No)” (F1001_02) (BIBB/BAuA 2011). However, this survey is only conducted every six years and the questions appear to be too narrow for our analysis, as, e. g. question F300 allows the mention of only one tool. Furthermore, the questions related to IT tools (F318/319) are not specific enough to differentiate between IT-aided tools and IT-integrated tools. Additionally, despite the large number of (20,036) completed interviews (Rohrbach-Schmidt/Hall 2013), it would be difficult to receive representative results about tools for every occupational group at the 5-digit level. Another promising method seems to be the analysis of job vacancy data (see Güntürk-Kuhl et al. 2017). However, there are no values available for KldB2010 so far. For the future, it might be worthwhile to combine this approach with the results from BERUFENET.

Table 2: List of digital tools categories and their utilization in occupations.

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

Note: For each of the three digital tool categories, the frequency of keywords and their usage across occupations are displayed. These results are obtained after applying text mining with automatic coding. Numbers of tools without matches in the digital tool catalog: 5,171; Number of occupations without any digital tool: 191.

Source: Own calculations of text mining applied to the BERUFENET.

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 referred to “PC work places” and, consequently, they are not marked as separate tools (e. g. cloud computing services, machine learning algorithms).

Based on the digital tools identified, we create an occupations-tools-matrix that allocates the number of digital tools to every single occupation and groups them by categories of IT-aided and IT-integrated tools. 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 a single occupation $occ8d$ (8-digit level) in 2016.

$$dtox_{c_{occ8d}} = \frac{\sum dto_{c_{occ8d}}}{\sum tools_{occ8d}}$$

where $dtox_{c_{occ8d}}$ is the *digital tools index* (category c) of individual occupation $occ8d$ in 2016, $\sum dto_{c_{occ8d}}$ is the number of digital tools (category c) of occupation $occ8d$ in 2016, and $\sum tools_{occ8d}$ is the number of all tools of occupation $occ8d$ in 2016. c represents the categories of digital tools: 1. *IT-aided digital tools*, 2.

IT-integrated digital tools, and 0. *Digital tools total* (1 + 2). *Occ8d* stands for the 8-digit level of KldB2010.¹¹

Administrative employment data are only available at higher aggregated levels, starting at the 5-digit level of the KldB2010. To link the *dtox* values to administrative employment data, we have to aggregate the *dtox* from the 8-digit level to the 5-digit level. For the transformation of $dtox_{c_{occ8d}}$ to $dtox_{c_{occ5d}}$, we use a procedure similar to that applied by Dengler et al. (2014) and Janser (2018): the *digital tools index* of the 8-digit occupations is added up, and the total is divided by the number of 8-digit occupations within the 5-digit occupation, or as the following formula:

$$dtox_{c_{occ5d}} = \frac{\sum dtox_{c_{occ8d}}}{N_{occ8d \in 5d}}$$

As the data of employees per occupation is only available at the 5-digit level, there is no way to apply an employment-weight at this stage of the process (see also Dengler et al. 2014). Therefore, we have to assume that the number of employees in individual 8-digit level occupations is equally distributed within the aggregate of the 5-digit level occupations (“equal distribution assumption”), as follows:

$$emp_{occ8d \in 5d} = \frac{emp_{occ5d}}{N_{occ8d \in 5d}}$$

where $emp_{occ8d \in 5d}$ is the estimated number of employees per 8-digit level occupation within the occupational group (5-digit level), emp_{occ5d} denotes the total number of employees within the occupational group (5-digit level) and $N_{occ8d \in 5d}$ stands for the number of occupations at the 8-digit level within the occupational group (5-digit level). Using the occupational group of “*Occupations in warehousing and logistics–skilled tasks*” as an example, Table 3 shows how this aggregation procedure is implemented in the *dtox* data.¹²

¹¹ Please note that there is only a weak relation between the number of tasks and the *dtox*. The corresponding correlation coefficient for the number of tasks and the $dtox_{total}$ is 0.222. Hence, the design of the *dtox* does not imply a bias due to the sole number of tasks of an occupation.

¹² The individual occupation of “Logistics assistant (51312–108)” is not included in the calculation of *dtox* because the BERUFENET contains only information about one tool of this occupation. Depending on the character of this one tool, the entire occupation would obtain a *dtox* of 1 (if the tool is IT-aided or IT-integrated) or 0 (it is not a digital tool), which would lead to a strong bias of the resulting aggregate at the 5-digit level.

Table 3: Exemplary aggregation procedure for *dtox* index.

Individual Occupation 8-digit level of KldB 2010 (ID + Title)	Occupational type 5-digit level of KldB 2010 (ID + Title)	No. of employees 5-digit level	No. of employees 8-digit level	$dtox_{IT-aid}$ 8-digit level	$dtox_{IT-aid}$ 5-digit level (aggregate)	$dtox_{IT-int}$ 8-digit level	$dtox_{IT-int}$ 5-digit level (aggregate)
51312–100 Order Picker	51312 Occupations in warehousing and logistics–skilled tasks	384,142	unobserved ↓ equal distribution assumption ↓ 64,023.7 per occupation at 8-digit level	0.17	0.21	0.08	0.09
51312–107 Receiving Department Clerk				0.17		0.17	
51312–109 Specialist - Logistics/ Materials Management				0.20		0.07	
51312–110 Dispatcher - Warehouse				0.60		0.00	
51,312–111 Specialist - Warehouse Logistics	51312–112 Warehouse Clerk			0.07	0.05	0.14	
51312–112 Warehouse Clerk						0.05	

Note: Aggregation of the individual occupations at the 8-digit level to 5-digit levels (KldB 2010) and the respective aggregation of the *dtox* index exemplarily for “Occupations in warehousing and logistics–skilled tasks”. The Appendix (Table 11) contains a comprehensive list of occupational segments sorted by their aggregated *dtox* value. Moreover, Table 12 provides an overview of the *dtox* index for different requirement levels.
Source: BERUFENET 2016, employment statistics of the Federal Employment Agency, own calculations.

Furthermore, 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.

2.2 Descriptive evidence

After having compiled information from different data sources,¹³ we now compares several characteristics between workers of the *latecomer*, *peloton* and *pioneer* establishments in Table 4. It can be seen that workers from *pioneers* are more qualified than workers from *latecomers*. Both the share of employees with high occupational requirement levels (experts and specialists) and the share of workers with high formal qualification levels (high-skilled workers) of *pioneers* exceed the employment shares of the *latecomers*. This pattern is also reflected in the tasks and tools distribution of the workforce. *Pioneers* employ more workers performing analytical and interactive tasks that work with IT-aided or IT-integrated digital work tools. In contrast, *latecomers* have more employees performing manual tasks. Between 2011 and 2016, the share of routine manual tasks in *latecomer* establishments decreased, whereas for both *latecomers* and *pioneers* the share of analytical tasks that are performed by the employees increased. The increase in analytical tasks in *latecomer* establishments is also associated with an increase in the share of IT-aided digital tools used by the workers. This workforce composition might simply be driven by the characteristics of the employer. We observe that workers of *pioneers* are disproportionately often employed in establishments of knowledge intensive services sectors and ICT. For example, a high share of *pioneer* establishments are represented in the “human health activities” sector and the sector conducting “computer programming, consultancy and related activities”. In contrast, *latecomers* are often establishments assigned to the “manufacture of machinery and equipment” sector and to “civil engineering”.¹⁴ Regarding the gender distribution, the share of female workers is higher among *pioneers*. In contrast, *latecomers* employ more foreign workers. The age distribution in the sample does not show heterogeneities as in 2011, either in *latecomers* or *pioneer* establishments, and the mean age of the workforce was 42 years. *Pioneers* more often employed

¹³ Some more variables (for instance, gross outputs) are gathered from the establishment panel of the IAB.

¹⁴ A summary of the ten most frequent sectors according to the divisions of the German Classification of Economic Activities across the three establishment types can be found in the Appendix Table 13.

Table 4: Sample means for workers in latecomer, peloton and pioneer establishments.

	Latecomers			Peloton			Pioneers		
	2011 (%)	2016 (%)	Δ (p.p.)	2011 (%)	2016 (%)	Δ (p.p.)	2011 (%)	2016 (%)	Δ (p.p.)
Share of workers by requirement level									
Unskilled/Semi-skilled worker	12.8	11.8	-1.0	8.8	8.4	-0.4	9.9	10.1	0.2
Skilled worker	70.3	69.4	-0.9	61.7	60.9	-0.9	62.3	61.1	-1.2
Specialist	11.5	12.8	1.2	13.8	15.0	1.3	14.2	14.7	0.5
Expert	5.4	6.1	0.7	15.7	15.7	0.0	13.6	14.1	0.4
Share of workers by skill level									
Missing	0.8	0.8	0.0	1.2	1.2	0.0	0.4	0.4	0.0
Low-skilled	6.5	6.5	0.0	3.8	3.8	0.0	4.6	4.6	0.0
Skilled	85.3	85.3	0.0	76.3	76.3	0.0	75.7	75.7	0.0
High-skilled	7.4	7.4	0.0	18.7	18.7	0.0	19.4	19.4	0.0
Share of female workers	18.0	18.0	0.0	35.0	35.0	0.0	30.3	30.3	0.0
Mean age (in years)	42	47	5	43	48	5	42	47	5
Share of temporary workers	2.5	2.7	0.2	3.0	2.6	-0.4	3.5	2.5	-1.0
Share of foreign workers	9.0	8.7	-0.4	5.9	4.8	-1.2	5.4	5.2	-0.2
Share of performed tasks									
Analytical tasks	16.6	17.1	0.4	25.8	26.1	0.3	26.0	26.3	0.3
Interactive tasks	4.5	4.3	-0.1	11.9	11.8	-0.1	10.8	10.9	0.1
Routine cognitive tasks	25.4	25.3	-0.1	29.9	29.9	0.0	31.9	31.8	-0.1
Routine manual tasks	22.2	21.5	-0.6	11.8	11.6	-0.1	13.6	13.5	-0.1
Non-routine manual tasks	31.4	31.8	0.4	20.6	20.6	0.0	17.8	17.6	-0.2
Total share of digital tools	22.5	22.8	0.3	32.7	32.8	0.1	33.2	33.2	0.0
Share of IT-aided digital tools	20.5	20.8	0.3	30.5	30.5	0.0	31.0	31.0	0.0

(continued)

Table 4: (continued)

	Latecomers				Peloton				Pioneers			
	2011 (%)	2016 (%)	Δ (p.p.)		2011 (%)	2016 (%)	Δ (p.p.)		2011 (%)	2016 (%)	Δ (p.p.)	
Share of IT-integrated digital tools	1.9	2.0	0.1		2.2	2.2	0.0		2.2	2.1	-0.1	
Share of workers by establishment size												
Small (1–49 workers)	56.8	55.0	-1.8		49.5	49.9	0.4		38.9	38.7	-0.2	
Medium (50–499 workers)	39.9	40.7	0.8		40.8	40.9	0.1		51.1	50.1	-1.0	
Large (500 and more workers)	3.3	4.4	1.1		9.7	9.2	-0.5		10.0	11.2	1.2	
Mean establishment size	97	104	7		252	256	4		250	276	26	
Share of workers by sector												
Non-knowledge intensive manufacturing	54.1	54.1	0.0		22.1	22.1	0.0		21.9	21.9	0.0	
Knowledge intensive manufacturing	12.8	12.8	0.0		10.0	10.0	0.0		13.4	13.4	0.0	
Non-knowledge intensive services	29.2	29.2	0.0		47.2	47.2	0.0		40.8	40.8	0.0	
Knowledge intensive services	3.0	3.0	0.0		17.6	17.6	0.0		17.8	17.8	0.0	
Information and communication technologies (ICT)	0.8	0.8	0.0		3.1	3.1	0.0		6.2	6.2	0.0	
Share of workers by type of the region												
Dense metropolitan areas	9.7	9.7	0.0		35.7	36.1	0.4		24.0	23.7	-0.3	
Metropolitan surroundings	52.7	52.7	0.0		33.7	33.9	0.2		40.7	40.6	-0.1	
Central cities in rural areas	19.1	19.3	0.2		16.8	16.3	-0.5		18.6	18.9	0.4	
Rural areas	18.5	18.3	-0.2		13.7	13.7	0.0		16.8	16.8	0.0	
Share of workers by federal state aggregates												
North	9.8	9.8	0.0		16.5	16.5	0.0		16.0	16.5	0.5	
West	30.0	30.0	0.0		31.2	31.1	-0.1		29.7	29.6	-0.1	

South	42.1	42.1	0.0	34.7	34.8	0.1	38.6	38.3	-0.4
East	18.0	18.0	0.0	17.7	17.7	0.0	15.7	15.7	0.0
Daily wages (in €, imputed and deflated)	88.9	98.3	9.4	104.1	113.6	9.4	104.5	115.7	11.2
Number of workers	11,539			48,426			31,017		
Number of establishments	280			862			383		

Note: The table shows several characteristics of the employees in the *latecomer*, *peloton* and *pioneer* establishments of the sample. The calculations above have a basis in weighted data.

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

workers with a fixed work contract; however, in 2016 the share of fixed work contracts decreased to the same level as present in *latecomer* establishments. Moreover, *pioneer* establishments are larger and record the highest employment growth rates, as the mean establishment size in 2011 was 250, which increased up to 276 in 2016. With respect to the regional allocation across the Federal States of Germany, *latecomers* are more often located in the Eastern states, whereas more *pioneers* can be found in the Northern states. Additionally, more *pioneers* are located in dense metropolitan areas and their surroundings. These differences in employer characteristics are also reflected in the mean wages of workers, i. e. workers of *pioneers* earn €105 per day in 2011, which is approximately 18 % more than the wages of *latecomers* (€89). In both establishment types the wage growth between 2011 and 2016 is approximately 10 %, as workers of *pioneers* earned €116 per day in 2016 and workers of *latecomers* earned €98. Controlling for these differences in the observed characteristics between the workers of *pioneers* and *latecomers* in the OLS regressions, we observe that this wage premium decreases to 2%.¹⁵

Note that the OLS results suffer from unobserved heterogeneity between workers. To circumvent this problem, and because we are interested in wage growth effects of digitalization, we apply a model using differences in the next section.

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 investments by establishments in new digital technologies on the wages of workers. We specifically investigate which groups of workers are positively or negatively affected by the digital transformation occurring in recent years. In addition to qualification, sex, age or sector affiliation, we also consider the role of the tasks that workers perform in their jobs and the role of the work equipment

¹⁵ The OLS wage-level results are not contained in the paper but are available upon request from the authors. It should be noted, however, that the estimated coefficient is statistically significantly different from zero at the 1 percent level, indicating a robust wage premium for *pioneers'* workers compared with *latecomers'* workers.

(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 establishments as shown above into *pioneers* (these establishments invest in new digital technologies between 2011 and 2016), *peloton* establishments (these establishments invest in digital technologies to a small extent) and *latecomers* (these establishments do not invest in new digital technologies and do not use them in 2016). This information is captured by dummy variables for the *peloton* and for *pioneers*, which we include in Mincer-type wage growth regressions, and *latecomers* are used as the reference group. We address time varying establishment- and worker-characteristics by including a battery of control variables; all time invariant characteristics are removed through differencing. Formally, the estimated model is as follows:

$$y_{iet} = \beta_0 + \beta_1 DPioneer_{iet} + \beta_2 DPeloton_{iet} + \beta_3 X_{iet} + \mu_i + \vartheta_e + \delta_t + \varepsilon_{iet} \quad (1)$$

where y_{iet} denotes the log wage of individual i in establishment e in year t . X_{iet} contains time-varying individual and establishment-related (individual) characteristics, such as individual ages, the digital tools index, the tasks index, (log) establishment size, (log) establishments' gross per-capita output and per-capita investments, and the shares of intermediate consumption,¹⁶ foreigners, female workers, highly skilled workers, temporary workers, etc. at the establishment level. All time constant individual characteristics, such as unobserved ability, ambition, and motivation, are contained in μ_i . They are removed by our approach, as are the time constant establishment characteristics ϑ_e (such as the location of the establishment or sector affiliation). δ_t captures general time shocks, and ε_{iet} represents erratic shocks. The effects of investments in new digital technologies at the establishment level are captured by the coefficient β . β_1 of the dummy variable $DPeloton_{iet}$ and β_2 of the dummy variable $DPioneer_{iet}$ capture the effects for being employed in a *peloton* or *pioneer* establishment relative to being employed in a *latecomer* establishment.

We estimate this wage equation for the aggregate as well as for different subgroups of workers (by sex, age, skill, sector, main tasks groups, digital tools

¹⁶ The information about gross outputs, investments and the share of intermediate consumption is imputed from the IAB establishment panel. More precisely, we build industry x region x establishment size x year cells in the establishment panel, collapse the means of the variables and transfer the information on a cell basis to our data set. Please note that the regression results are robust with regard to the use of the median (instead of the mean) or more complex imputation procedures.

categories and by interactions of sector and skill, sector and tasks, etc.) The results of these estimates give us an idea of which workers suffer or benefit from the digital transformation in terms of wages.

3.2 Estimation results

Table 5 shows the results of the individual fixed effects estimates.¹⁷ Column 1 contains the results for the sample of all workers. The wage growth differential of working for a *pioneer* instead of a *latecomer* is 0.8 percentage points between the years 2011 and 2016. This effect is moderate but positive and is 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/

Table 5: Results of the fixed-effects estimates for all workers and specific subgroups.

Variable	Baseline	Gender		Skill		
	All workers	Male workers	Female workers	Low- skilled workers	Skilled workers	High- skilled workers
	(1)	(2)	(3)	(4)	(5)	(6)
Dummy indicator: Wage growth effect of <i>peloton</i> establishments vs. <i>latecomers</i>	0.006***	0.008***	−0.002	0.019**	0.006***	−0.003
Dummy indicator: Wage growth effect of <i>pioneers</i> vs. <i>latecomers</i>	0.008***	0.011***	−0.002	0.036***	0.010***	−0.007
N	179,357	127,963	51,421	9,673	132,895	36,789
R-squared	0.309	0.329	0.274	0.362	0.356	0.229
F	1189.6	962.6	328.8	75.0	1124.5	161.1

Note: The time dummy for the year 2016, individual age effects (squared; interaction effects with being in the highest age category), individual shares of digital tools, individual share of analytical tasks, interactive tasks, routine-cognitive tasks, routine-manual tasks, and further establishment controls (log size (linear + squared), establishment's shares of digital tools and tasks, mean age of workers, share of female workers, share of foreign workers, share of temporary workers, share of high-skilled workers, log gross per-capita output (lin. + squared)), log per-capita investments (lin. + squared) and share of intermediate consumption are included; ***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.

¹⁷ A more detailed result table can be found in the Appendix Table 15.

Restrepo 2017) and supports those papers that suggest positive effects on wages (for instance, Graetz/Michaels 2015). Note, however, that the mentioned studies investigate the effects of industrial robots on wages. In our view, this technology is not new because many of these industrial robots were introduced in the 1980s and 1990s. As a consequence, our results 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, such as 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 paper¹⁸; hence, possible selection effects could explain a part of the positive wage growth effects. This would be the case if *pioneers* lay off low-performance workers more often than *latecomers*. 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, i. e. 67.3 % of *pioneer* workers and 68.4 % of *latecomer* workers survive this selection step. That could be understood as a hint that selection effects do not largely bias the presented results. Digging deeper, we investigate which groups of workers are predominantly affected by our selection. Columns 1 and 2 of Appendix Table 14 show mean wages and observation numbers of different skill groups in *latecomer*, *peloton* and *pioneer* establishments. For all 735 low-skilled *latecomer* workers (column 2), the mean wage in 2011 is €81.78 (column 1). The balancing of the sample decreases the number of workers to 475 workers (column 4) and increases the mean wage by 6 % to €86.82 (column 3). Here, the impact of the selection on wages and the number of low-skilled workers is slightly lower than in *peloton* and *pioneer* establishments (column 5 and column 6). For the other skill groups, however, the balancing has comparably the same effects.¹⁹ Column 1 of Table 5 demonstrates that the wage growth effect is higher in *peloton* establishments compared with *latecomer* establishments. The effect amounts to 0.6 percentage points. Note that both effects—for *peloton* establishments as well as for *pioneers*—are highly robust with regard to inclusion or exclusion of further control variables (for instance, we additionally included controls for occupational changes on the individual as well as the establishment level).

Results by sex, skill and age: The remainder of Table 5 depicts the estimation results for specific worker groups. Columns 2 and 3 show that the wage growth

¹⁸ For the effects of new digital technologies on employment at the individual level, see Arntz et al. (2018b).

¹⁹ Nevertheless, we carry out robustness checks in which we relax our restriction on establishment stayers (see the last paragraph of Section 3).

effect of investments into new digital technologies is more pronounced for male workers than for female workers. For male workers, it amounts to 1.1 percentage points and is statistically highly significant. For female workers, it is -0.2 percentage points and is not statistically 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 for different skill groups, let us first summarize the 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 have a gain in earnings. Interestingly, we find the largest positive effect for low-skilled workers (3.6 percentage points, see column 4). For skilled workers, it is 1 percentage point (see column 5), and for high-skilled workers, it amounts to -0.7 percentage point but is not statistically significant (see column 6).²⁰ We interpret these results in such a way that it benefits low-skilled and skilled establishment stayers when establishments invest in new digital technologies.

For this analysis, however, we compare low-skilled stayers in *pioneers* with low-skilled stayers in *latecomers* and skilled stayers in *pioneers* with skilled stayers in *latecomers*. 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 establishment.²¹

Regarding age effects, it can be seen from Table 6 that younger workers especially benefit from being employed in a *pioneer* compared to being employed in a *latecomer*.²² The wage growth effect amounts to 2.6 percentage points. For middle age and older workers, the effect is only 0.6 percentage points to 0.7 percentage points. Since accumulation of establishment-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 establishments.

20 Similar results arise when differentiating 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 are not statistically significantly different from zero at a 5 percent level. These results are not contained in the paper but are available from the authors upon request.

21 We examine this issue in a plausibility check presented below.

22 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 upon request.

Table 6: Results of the fixed-effects estimates for different age groups of workers.

Variable	Age		
	Younger workers (< 30 years) (1)	Medium-aged workers (30–49 years) (2)	Older workers (≥ 50 years) (3)
Dummy indicator: Wage growth effect of <i>peloton</i> vs. <i>latecomers</i>	0.006	0.005**	0.009***
Dummy indicator: Wage growth effect of <i>pioneers</i> vs. <i>latecomers</i>	0.026***	0.006**	0.007**
N	24,162	108,212	46,983
R-squared	0.493	0.282	0.158
F	456.1	661.1	169.3

Note: The time dummy for the year 2016, individual age effects (squared; interaction effects with being in the highest age category), individual shares of digital tools, individual share of analytical tasks, interactive tasks, routine-cognitive tasks, routine-manual tasks, and further establishment controls (log size (linear + squared), establishment's shares of digital tools and tasks, mean age of workers, share of female workers, share of foreign workers, share of temporary workers, share of high-skilled workers, log gross per-capita output (lin. + squared)), log per-capita investments (lin. + squared) and share of intermediate consumption are included; a more detailed result table containing the effects of the covariates is available from the authors on request. ***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 ($dtox_{IT-AID}$), i. e. tools such as computers, printers, and electronic machines, that are not explicitly dedicated to an industry 4.0 feature and IT-integrated tools ($dtox_{IT-INT}$), i. e. tools 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 $dtox_{IT-AID}$ distribution in 2011. The average share of IT-aided work equipment is 29.4 % in 2011. The median is somewhat lower at 25.6 %. The category "low" comprises workers with a below the median share of $dtox_{IT-AID}$. The category "middle" comprises workers with a $dtox_{IT-AID}$ share between the median and the 75th percentile of the distribution (this is at 49.8 %) and the category "high" comprises workers with a $dtox_{IT-AID}$ share of the 75th percentile or higher.

The same categorization is done for $dtox_{IT-INT}$. Here, the median in 2011 is at 0.5 % and the 75th percentile of the distribution is at 3.5 percentage. We see that

Table 7: Results of the fixed-effects estimates for digital tool groups.

Variable	IT-aided digital tools			IT-integrated digital tools		
	<i>dtox</i> _{IT-AID} low (1)	<i>dtox</i> _{IT-AID} medium (2)	<i>dtox</i> _{IT-AID} high (3)	<i>dtox</i> _{IT-INT} low (4)	<i>dtox</i> _{IT-INT} medium (5)	<i>dtox</i> _{IT-INT} high (6)
Dummy indicator: Wage growth effect of <i>peloton</i> establishments vs. <i>latecomers</i>	0.013***	−0.000	−0.003	0.002	0.024***	−0.0063*
Dummy indicator: Wage growth effect of <i>pioneers</i> vs. <i>latecomers</i>	0.017***	0.003	−0.008*	0.005	0.023***	−0.0008
N	89,707	41,559	48,091	79,913	54,748	44,696
R-squared	0.365	0.296	0.261	0.310	0.3180	0.3085
F	788.6	259.2	264.2	534.6	392.47	320.11

Note: The time dummy for the year 2016, individual age effects (squared; interaction effects with being in the highest age category), individual shares of digital tools, individual share of analytical tasks, interactive tasks, routine-cognitive tasks, routine-manual tasks, and further establishment controls (log size (linear + squared), establishment's shares of digital tools and tasks, mean age of workers, share of female workers, share of foreign workers, share of temporary workers, share of high-skilled workers, log gross per-capita output (lin. + squared)), log per-capita investments (lin. + squared) and share of intermediate consumption are included; a more detailed result table containing the effects of the covariates is available from the authors on request. ***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.

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 7 presents the results for the three *dtox*_{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 (1.7 percentage points, see column 1). The wage growth effect is even negative (but only significant at a 10 percent level) 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 the 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 Tables 16).

Before shedding light on these unexpected results, we turn to the three $dtox_{IT-INT}$ groups on the right panel of Table 7. Here, we see the largest wage growth effect for workers of the medium category (2.3 percentage points, see column 5). 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.

Sector-specific results: One could argue, that comparing, e. g. workers primarily using non-digital working tools between *latecomers* and *pioneers* could be misleading when *pioneers* are typically (e. g.) large, modern IT-establishments and *latecomers* are typically (e. g.) small construction establishments. In the former, it would be quite unusual that workers primarily use non-digital working tools, while this is entirely normal in the latter. Having this battery of control variables included in the fixed effects approach 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 8 shows that the wage growth effects for working for a *pioneer* vs. a *latecomer* are significantly positive in the sector aggregates knowledge intensive manufacturing (2.2 percentage points, see column 2; e. g. car manufacturers or machine manufacturers) and non-knowledge intensive services (4.3 percentage points, see column 3; e. g. wholesalers, logistics, restaurants). Among ICT establishments, the effect is also positive but is smaller and significantly different from zero at the 10 percentage level only (see column 5). By contrast, it is negative in knowledge intensive services (−1.8 percentage points, see column 4; e. g. banks, insurances, scientific services).

After further analyses, Table 9 shows the estimated coefficients of the treatment variable 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 is 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. In knowledge intensive services, we observe that the negative wage growth effect can mostly be explained by the effect for high-skilled workers, i. e. it is negative (−4.8 percentage points) and statistically significant at the 1 percent level.

Repeating the $dtox_{IT-INT}$ groups analyses separated by sectors (see Table 10), we observe significant effects only for the low and intermediate IT-integrated 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 helps to explain the higher wage growth of the *pioneers'* workers, especially within knowledge intensive services. By contrast, in knowledge intensive manufacturing, the positive effect is detected for workers who do not use IT-integrated working tools or who only use it to a small extent.

Table 8: Results of the fixed-effects estimates for different sectors.

Variable	Sectors				
	non- knowledge intensive manufacturing (1)	Knowledge intensive manufacturing (2)	non- knowledge intensive services (3)	knowledge intensive services (4)	ICT (5)
Dummy indicator: Wage growth effect of <i>peloton</i> establishments vs. <i>latecomers</i>	0.005	0.004	0.040***	−0.019**	0.012
Dummy indicator: Wage growth effect of <i>pioneers</i> vs. <i>latecomers</i>	−0.003	0.022***	0.043***	−0.018**	0.013*
N	39,830	55,243	22,114	34,702	27,468
R-squared	0.342	0.321	0.345	0.300	0.292
F	296.4	442.6	190.7	232.8	177.9

Note: The time dummy for the year 2016, individual age effects (squared; interaction effects with being in the highest age category), individual shares of digital tools, individual share of analytical tasks, interactive tasks, routine-cognitive tasks, routine-manual tasks, and further establishment controls (log size (linear + squared), establishment's shares of digital tools and tasks, mean age of workers, share of female workers, share of foreign workers, share of temporary workers, share of high-skilled workers, log gross per-capita output (lin. + squared)), log per-capita investments (lin. + squared) and share of intermediate consumption are included; a more detailed result table containing the effects of the covariates is available from the authors on request. ***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.

Similar results are obtained for the usage of IT-aided working tools (by repeating the $dtox_{IT-AID}$ groups analyses separated for sectors²³). In terms of wages, it seems that the usage of work-equipment is polarized in the sense that people using non-digitalized and high-digitalized work equipment benefit from the establishments' digital transformation, while this is not the case for workers using equipment with an intermediate share of digitalization. To recheck this finding, we change our point of view and focus on the employees in *pioneers*.

²³ The results of this analysis are not documented in the paper but are available from the authors upon request.

Table 9: Estimated wage growth effect for skill groups within sector aggregates.

Sector aggregates	Skill level	Wage growth effect of <i>pioneers</i> vs. <i>latecomers</i>
Non-knowledge intensive manufacturing	low	0.007
	medium	−0.001
	high	−0.021
Knowledge intensive manufacturing	low	0.030*
	medium	0.023***
	high	0.007
Non-knowledge intensive services	low	0.105***
	medium	0.040***
	high	0.047
Knowledge intensive services	low	−0.074
	medium	0.005
	high	−0.048***
ICT	low	0.059
	medium	0.013
	high	0.001

Note: The table shows estimated coefficients for a dummy indicator “wage growth effect of *pioneers* vs. *latecomers*” for skill groups by sectors and different skill levels; we use the same control variables as documented above; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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

Who benefits within *pioneers*? To measure wage growth effects for workers within pioneers we interact the dummy variable that indicates the affiliation to a specific group (for instance skilled or high-skilled) with the year dummy for 2016.²⁴ Starting with differences between skill groups, it is worth noting that all effects are insignificant at a 5 percent level (in non-knowledge intensive manufacturing establishments, there is a positive effect being significantly different from zero at the 10 percent level: 1.4 percentage points for skilled workers relative to low-skilled workers; in knowledge intensive manufacturing and knowledge intensive services there are two negative effects for skilled workers relative to low-skilled workers that amounts to −1.9 percentage points and −2.5 percentage points, respectively). That means that low-skilled, skilled and high-skilled workers within *pioneers* 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

²⁴ The results of this analysis are not documented in the paper but are available from the authors upon request.

Table 10: Estimated wage growth effect for digital tool categories within sector aggregates.

Sector aggregates	<i>dtoxit-int</i>	Wage growth effect of <i>pioneers</i> vs. <i>latecomers</i>
Non-knowledge intensive manufacturing	low	−0.005
	medium	0.011*
	high	−0.014
Knowledge intensive manufacturing	low	0.015***
	medium	0.042***
	high	0.007
Non-knowledge intensive services	low	0.020
	medium	0.026
	high	0.062***
Knowledge intensive services	low	−0.011
	medium	−0.023
	high	−0.012
ICT	low	0.018
	medium	0.004
	high	0.023

Note: The table shows estimated coefficients for a dummy indicator “wage growth effect of *pioneers* vs. *latecomers*” for digital tool categories by sectors and different tools categories; we use the same control variables as documented above; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: “IAB-ZEW Labour Market 4.0” establishment survey, BeH, BERUFENET, IAB Establishment Panel, own calculations.

is therefore less attributed to differing effects for skill groups within *pioneers* but is more attributed to differing wage growth rates in establishments without new digital technology investments (regarding *latecomers*, 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 slightly positive effects in the amount of 1 percentage point (but statistically significantly different from zero at a ten percent level, only) for workers in *pioneers* if they operate with IT-aided tools and a smaller amount of IT-integrated tools. Our results show that working with many IT-integrated tools has no positive impact on employee wage growth. This could be due to learning effects that only increase productivity with a time delay when new tools are used. We will take a closer look at this effect in our future research.

How important are selection effects? As discussed above, one could argue that possible selection effects could explain a part of the positive wage growth effects. To take this into account, we abandon the restriction of the sample to employees who stayed with the same employer, which means that we include

establishment leavers in our sample.²⁵ This increases our sample size from approximately 90,000 to 115,000 individuals. The disadvantage of this approach is that we do not know whether the person is switching to a *pioneer*, *peloton* or *latecomer* establishment. Nor do we know the reason for leaving the establishment. Due to this unobservable heterogeneity, we think that the restriction on establishment stayers provides a clearer picture. However, repeating our analyses with the extended sample, Appendix Table 17 shows that for the aggregate as well as for specific subgroups, the positive effects are increasing. The wage growth differential of working or having worked, respectively, for a *pioneer* instead of a *latecomer* (see column 1) is now 1.7 percentage points between the years 2011 and 2016 (instead of 0.8 percentage point for establishment stayers). The effect for male workers (column 2) is now 2.1 percentage points (instead of 1.1 percentage points), and for female workers (column 3), it is 0.7 percentage points (instead of - 0.2 percentage points). Turning to the skill groups (columns 4–6), the estimates corroborate our finding that digitalization is beneficial, especially for low-skilled and skilled workers. The wage growth differential is 4.1 percentage points for low-skilled, 1.7 percentage points for skilled and - 0.1 percentage points (but statistically not significant) for high-skilled workers. Without wanting to overinterpret the results, there seems to be a positive effect that can be transferred from *pioneers* to other establishments. The reasons for this will be investigated in further analyses. The repetition of the other specifications documented above confirms the robustness of our results (these results are not included in the paper due to lack of space but are available from the authors upon request).

4 Conclusions

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

To fill this gap, this paper uses a novel linked employer–employee data set that contains detailed information on establishments’ technological upgrading

²⁵ Besides establishment leavers, there are other groups that are excluded by our restriction, i. e. employees who no longer appear in the data (because they leave the labor market or change to self-employment) and employees who enter a *pioneer*, *peloton* or *latecomer* establishment after 2011. With the first group, wage analyses make no sense, as they are not observable. The second group of new entrants is a special sample (often young, at the beginning of their career with special wage growth paths). To limit the length of this paper, we do not look at this group here and reserved this for further analyses.

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 digitalization at both the establishment level and the worker level. The data allow us to investigate the impact of technology investments on the remuneration of the employees within these establishments.

We use the data to categorize the establishments into the three following categories: *digital pioneers*, who invested significantly in new digital technologies between 2011 and 2016, the *digital peloton* of establishments that have already invested in new digital technologies to a limited extent, and *digital latecomers*, who have not been investing in such technologies during our observation period from 2011 to 2016. We estimate individual fixed effects regressions for the aggregate of workers as well as for different subgroups of workers (by sex, age, skill, sector, main tasks groups, digital tools categories and by interactions of sector and skill, sector and tasks, etc.) and include the establishment categories as dummy variables in the wage regression to identify the effect of the establishment's digital transformation on the wages of the employed workers. To obtain valid results, we focus on the group of full-time employed establishment stayers. In a robustness check, we also include establishment leavers in our analyses. The paper does not include an analysis of the wage effects for establishments' new entrants or part-time workers. The results of our estimates, however, give us an idea of which workers suffer or benefit from the digital transformation in terms of wages.

For the aggregate, the wage growth effect of working for a *pioneer* instead of working for a *latecomer* is 0.8 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 subgroups indicate that digitalization especially benefits younger workers, low-skilled and skilled workers when establishments 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 *pioneers* but is more attributed to differing wage growth rates in *latecomers*. Regarding *latecomers*, we observe that the wage growth rates increase with the skill level of the employees, while this is not the case within *pioneers*. In our opinion, these results suggest that workers, who are often perceived as the losers of the digital transformation in terms of employment, might nevertheless benefit in terms of wages. As this study has also shown, there are still many interesting labor market impacts to analyze in the area of digitalization. The question of how investments in digital technologies affect employment development seems to us to be a particularly important issue.

Two in-depth papers will provide more information on this topic at establishment level (Arntz et al. 2018a) and at worker level (Arntz et al. 2018b).

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Appendix

Table 11: Occupational segments sorted by $dtox_{total}$ value.

KldB2010	Occupational segment	$dtox_{total}$	$dtox_{IT-AID}$	$dtox_{IT-INT}$
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 organization	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 the 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, gastronomy and 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

Note: The table presents the ranking of occupational segments with the highest $dtox_{total}$ values with respect to KldB2010, 8-digit level. The first value of column $dtox_{total}$ shows that 51.7 % of tools in business related service occupations are digital tools. This value is the total from the two following columns, of which approximately 51.0 % are IT-aided tools ($dtox_{IT-AID}$) and 0.7 % are IT-integrated tools ($dtox_{IT-INT}$). 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 %). 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 yet cover those tools.

Source: BERUFENET 2016, own calculations.

Table 12: Digital-tools index $dtox$ aggregated by requirement levels.

KldB 2010 5th digit	Requirement level	$dtox_{total}$	$dtox_{IT-AID}$	$dtox_{IT-INT}$
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

Note: With a $dtox_{total}$ 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 $dtox_{IT-AID}$ also follows this pattern, whereas the distribution of IT-integrated tools is not yet as polarized ($dtox_{IT-INT}$ Max: 0.023 (Specialist)/Min: 0.014 (Unskilled/Semi-skilled workers)). The calculations are weighted by the number of employees within each requirement level group.

Source: BERUFENET 2016, own calculations.

Table 13: Sectors ranked by frequency for latecomer, peloton and pioneer establishments.

Division No.	Classification of Economic Activities (Edition 2008, wz08)	Latecomers	Peloton	Pioneers
10	Manufacture of food products	7	9	10
22	Manufacture of rubber and plastic products	–	8	8
24	Manufacture of basic metals	–	10	–
25	Manufacture of fabricated metal products, except machinery and equipment	4	–	7
26	Manufacture of computer, electronic and optical products	2	5	1
27	Manufacture of electrical equipment	3	4	3
28	Manufacture of machinery and equipment n.e.c.	1	2	6
29	Manufacture of motor vehicles, trailers and semi-trailers	5	7	5
37	Sewerage	9	–	–
42	Civil engineering	6	–	–
43	Specialized construction activities	8	–	–
46	Wholesale trade, except of motor vehicles and motorcycles	–	–	9
52	Warehousing and support activities for transportation	10	–	–
62	Computer programming, consultancy and related activities	–	6	4

(continued)

Table 13: (continued)

Division No.	Classification of Economic Activities (Edition 2008, wz08)	Latecomers	Peloton	Pioneers
84	Public administration and defense; compulsory social security	–	3	–
86	Human health activities	–	1	2

Note: The ranking indicates the ten most frequent sectors of the establishments. If no number is indicated, the sector is not among the largest ten sectors for this establishment category. The sectors are labeled according to the division (2-digit) of the German Classification of Economic Activities (Edition 2008, WZ08).

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

Table 14: Sample selection process due to the construction of a balanced panel.

Establishments	Skill group	Unbalanced panel		Balanced panel		Differences (in percent)	
		(1)	(2)	(3)	(4)	(5)	(6)
		Mean wage (in €)	N	Mean wage (in €)	N	Mean wage	Number of workers
Latecomer	low	81.78	735	86.82	475	6.2	–35.4
Peloton	low	84.95	3,413	92.91	1,920	9.4	–43.7
Pioneer	low	85.31	2,322	91.58	1,398	7.3	–39.8
Latecomer	medium	89.35	13,586	93.65	9,132	4.8	–32.8
Peloton	medium	94.00	59,963	100.53	36,131	7.0	–39.7
Pioneer	medium	97.78	35,114	102.67	22,535	5.0	–35.8
Latecomer	high	143.97	3,255	150.97	1,932	4.9	–40.6
Peloton	high	149.67	19,685	158.55	10,375	5.9	–47.3
Pioneer	high	154.79	12,885	162.22	7,084	4.8	–45.0

Note: The table shows the impact of balancing the panel on wages and observation numbers separated for skill groups across different types of establishments.

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

Table 15: Results of the fixed-effects estimates for all workers and specific subgroups.

Variable	Baseline		Gender		Skill			
	All workers	(1)	Male workers	Female workers	Low-skilled workers	Skilled workers	High-skilled workers	
		(1)	(2)	(3)	(4)	(5)	(6)	
Dummy indicator: Wage growth effect of <i>peloton</i> establishments vs. <i>latecomers</i>	0.006***		0.008***	-0.002	0.019**	0.006***	-0.003003	
Dummy indicator: Wage growth effect of <i>pioneers</i> vs. <i>latecomers</i>	0.008***		0.011***	-0.002	0.036***	0.010***	-0.007007	
Establishment's share of digital tools (<i>dtox_{IT,AID}</i>)	0.151***		0.204***	0.010	0.254**	0.064**	0.397*****	
Establishment's share of digital tools (<i>dtox_{IT,INT}</i>)	-0.241**		-0.388***	-0.179	0.493	0.147	-1.047*****	
Establishment's share of analytical tasks	0.058		0.036	0.113	0.227	0.148***	-0.291*****	
Establishment's share of interactive tasks	-0.224***		-0.191***	-0.331***	-0.361*	-0.134**	-0.485*****	
Establishment's share of routine-cognitive tasks	-0.169***		-0.137***	-0.350***	-0.148	-0.122***	-0.477*****	
Establishment's share of routine-manual tasks	-0.080**		-0.048	-0.214**	0.087	-0.029	-0.244*	
Establishment's share of female workers	0.003		-0.000	0.001	0.068	0.027	-0.05303	
Individual share of analytical tasks	0.069***		0.077***	0.021	0.288***	0.063***	0.001001	
Individual share of interactive tasks	0.058*		0.067*	0.034	0.291	0.012	0.067067	
Individual share of routine-cognitive tasks	0.021		0.007	0.046	0.103	0.028	-0.038038	
Individual share of routine-manual tasks	-0.006		-0.014	0.054	0.126*	-0.013	-0.121012	
Individual share of digital tools (<i>dtox_{IT,AID}</i>)	0.056***		0.043***	0.106***	-0.067	0.062***	0.07878	
Individual share of digital tools (<i>dtox_{IT,INT}</i>)	0.043		0.029	0.073	1.118**	0.033	-0.018018	
Constant	9.226***		9.587***	9.266***	12.979***	7.831***	12.716*****	
N	179,357		127,963	51,421	9,673	132,895	36,789	
R-squared	0.309		0.329	0.274	0.362	0.356	0.229	
F	1189.6		962.6	328.8	75.0	1124.5	161.1	

Note: The 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 per-capita output (lin. + squared)), log per-capita investments (lin. + squared) and share of intermediate consumption are included; ***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.

Table 16: Estimated wage growth effect for different occupational main task groups.

Variable	analytical (1)	interactive (2)	routine- cognitive (3)	routine- manual (4)	non-routine manual (5)
Dummy indicator: Wage growth effect of <i>pioneers</i> vs. <i>latecomers</i>	−0.007	−0.018	0.025***	0.001	0.012*

Note: The table shows estimated coefficients for a dummy indicator “wage growth effect of *pioneers* vs. *latecomers*” for different occupational task groups; we use the same control variables as documented above; ***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.

Table 17: Estimated wage growth effect for the sample including establishment leavers.

Variable	Baseline	Gender		Skill		
	(1)	(2)	(3)	(4)	(5)	(6)
	All workers	Male workers	Female workers	Low-skilled workers	Skilled workers	High-skilled workers
Dummy indicator: Wage growth effect of <i>pioneers</i> vs. <i>latecomers</i>	0.017***	0.021***	0.007*	0.041***	0.017***	−0.001

Note: The table shows estimated coefficients for a dummy indicator “wage growth effect of *pioneers* vs. *latecomers*” for the sample of establishment stayers and leavers for all workers and specific subgroups; we use the same control variables as documented above (see, e. g. Table 5); ***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.