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DISCUSSION PAPER SERIES

IZA DP No. 16062

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APRIL 2023

ISSN: 2365-9793

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ABSTRACT

The Pandemic Push: Digital Technologies and Workforce Adjustments*

Based on a unique survey and administrative employer-employee data, we show that the COVID-19 pandemic acted as a push factor for the diffusion of digital technologies in Germany. About two in three firms invested in digital technologies, in particular in hardware and software to enable decentralized communication, management and coordination. The investments encouraged additional firm-sponsored training despite pandemic-related restrictions indicating that investments in digital technologies and training are complements. We then demonstrate that the additional investments helped firms to insure workers against the downturn during the pandemic. Firms that made additional investments relied less on short-time work, had more of their regular employees working normal hours and had to lay off fewer marginal workers. Male, younger and medium-skilled workers benefitted the most from the insurance effect of digital investments.

JEL Classification: D22, E22, J23, J63
Keywords: innovation, digital technologies, COVID-19, pandemic, investment, training, employment, worker flows

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* We thank Bernd Fitzenberger, Terry Gregory, Eduard Storm and participants at the IAB-LISER Conference, the TASKS VI Conference, the IWH-IAB Workshop, the 14th Interdisciplinary PhD-Workshop "Perspectives on (Un-) Employment" and seminars at the IAB and the FAU Erlangen-Nürnberg for useful comments and suggestions. We are also grateful to Britta Matthes, Michael Stops and Franziska Bruns for providing the data on screen work.

1 Introduction

The COVID-19 pandemic moved much of the world online with internet traffic expanding by up to 60% in some countries (Baruffaldi et al., 2020). Yet, the disruption of supply chains (Bonadio et al., 2021), mitigation measures to contain it and consumers' response to the risk of infection (Famiglietti and Leibovici, 2022) plunged the economy into a deep recession threatening the survival of many firms and jobs (Chetty et al., 2020). In its wake, families had to rearrange their division of labor (Albanesi and Kim, 2021), employees shifted to work from home (Bartik et al., 2020), consumers went online and firms adopted new business models and work organization (Alipour et al., 2021). Some of these changes are here to stay and leave a deep imprint on the labor market and the economy more broadly.

This paper investigates whether the pandemic was a push factor for the digital transition. We first ask whether and which firms invested in digital technologies during, but also *because* of the pandemic; and if so, what type of digital tools they invested in. Investments alone might not be sufficient to make productive and efficient use of digital technologies. Equally important is that the workforce is equipped with the skills and know-how to use and work with the new technical capabilities. We explore whether firms report a higher need for employee training and actually offered more employer-sponsored training despite pandemic restrictions and the economic downturn. Finally, we investigate whether digital investments had an effect on employment and wages of employees during the recession and which groups of workers were most affected.

In normal times, uncertainty – with respect to the duration and severity of the pandemic, but also its longer-term economic consequences – reduces incentives to invest because expected returns decrease and the option value of waiting increases (see, e.g., Bloom et al., 2007; Christiano et al., 2014). And indeed, the severe recession in 2020 dramatically increased economic uncertainty for many firms (Altig et al., 2020). Yet, firms also face lower opportunity costs of time and resources, which is one reason recessions are periods of creative destruction where painful adjustments, but also technological and skill upgrades, are made (Hershbein and Kahn, 2018; Chernoff and Warman, 2022). Moreover, the pandemic was special in the sense that it required firms to substitute for many personal interactions in their day-to-day operations. The widespread use of remote work is one indication that firms indeed adjusted their workflows (Bloom et al., 2020). Digital technologies provide important tools for working and managing remotely: collaboration software to hold meetings, cloud computing to share files, online management tools to coordinate activities and tasks. These tools further require the right infrastructure including hardware, secure access and data protection that firms might need to invest in or expand.

How firm investments respond to the pandemic is thus not clear ex ante: while digital technologies enable firms to adapt and possibly upgrade their business operations, the uncertainty might have also hampered or delayed investments. Moreover, firms might have responded very differently to the situation with some investing and others not. As such, the pandemic might have increased or reduced the digital divide between firms (see, e.g., Forman and Goldfarb, 2005; Rückert and Weiss, 2020). The digital divide would decline if the pandemic induced firms with few digital tools to catch up to their digitally more advanced peers. If, instead, firms with a good digital infrastructure invest more in additional digital tools, the digital divide could increase – with distributional consequences for firm pay and working conditions in the long-run.[1]

Investments in new technology require some adjustment in the organization of work and a potential need to train employees. Depending on whether the investments are labor-replacing or labor-enhancing, training might be a complement or substitute for investments (Dixon et al., 2019; Brunello et al., 2023). Moreover, investments might stabilize or increase employment if they enable firms to grow and take advantage of new business opportunities. They might decrease or replace workers if the investments take over tasks previously performed by humans. Little is known about which factor has dominated during the pandemic and which workers were most affected by it.

Our analysis links a unique establishment survey that was conducted during the pandemic with administrative matched employer-employee data from Germany.[2] Germany provides an interesting case study because it has lagged behind the broad diffusion of digital technologies. The survey questions used in this paper were designed by the authors and fielded to around 2,000 establishments in February 2021. Our survey elicits information on whether establishments had recently invested in eight types of digital technologies: hardware (like laptops or cameras), software for communication (like MS Teams), software for collaboration (like Google docs), remote access, faster internet, data protection and cyber-security, IT personnel and other technologies. The survey also asked establishments about their training needs and firm-provided training, their economic situation and how much they relied on working-from-home. We merge this information to administrative data including detailed information on the workforce and wages, industry and location.

The paper has four main findings. First, two out of three firms invested in digital technologies in the first year of the pandemic and about 50% invested *because* of the pandemic. Investing firms are typically larger, pay higher wages, have a more educated workforce and belong to knowledge-intensive sectors than firms that did not invest. That a considerable share of firms invested because of the pandemic is evidence that the pandemic was indeed a push factor for the digital transition because many firms indeed undertook

[1] Areas with higher levels of pre-pandemic IT capital showed more resilience during the pandemic in the U.S. (Oikonomou et al., 2023) and Germany (Ben Yahmed et al., 2022).

[2] While the survey explicitly samples establishments, we will interchangeably refer to them as plants, companies or firms.

investments despite the looming uncertainty. At the same time, the pandemic also increased the digital divide between firms, as investors were less commonly found among small- and medium-sized firms and firms in traditional manufacturing or low-skilled services. Once we control for workforce composition, industry and firm size, we see no relationship between firms that pay higher wages and the probability to invest in digital technologies.

Second, we demonstrate that training the workforce to use digital tools is an important complement to investments in digital tools. Investing firms report additional training needs, especially with respect to skills in online communication and cooperation followed by management skills, planning and organization, data protection and IT skills. Firms that invested because of the pandemic report having substantially more training needs than firms that did not invest in digital tools because of the pandemic. Most firms also increased employer-provided training in the mentioned areas despite the difficulties to organize training sessions and workshops. These results confirm that investments and training are strong complements in order to make productive use of the new technologies.

Third, we show that investing firms were better able to insure their employees against the economic shock of the pandemic. For both investing and non-investing firms, the pandemic initially led to a sharp reduction in total employment followed by a recovery towards the end of 2020. Yet, there are sizable differences by type of employees. Germany has a generous short-time work scheme; firms could reduce the working hours of their regular employees with the salary heavily subsidized by the Federal Employment Agency. Our results show that investing firms relied less on short-time work for their regular employees than non-investing firms. As a consequence, investing firms kept more of their regular employees working normal hours without salary loss. Moreover, the investments did not only benefit the regular workforce, but also marginal workers who enjoy weaker employment protection and are more vulnerable to being laid off during economic downturns. Investing firms were more likely to keep their marginal workers than non-investing firms. As we see smaller negative effects for both regular employees and marginal workers, these results cannot be explained by investing firms substituting marginal workers for regular employees. Our results support the view that technological change is often complementary to labor; in our case, it helped investing firms to avoid job disruptions and stabilize employment relationships during a severe recession and demand disruptions (Autor, 2015; Bessen, 2019).

Fourth, we find no effects on firm wages even conditional on workforce composition. We find some indication that firms postponed salary increases but the postponement was equally common in investing and non-investing firms. Like other studies on the German labor market, we find that employment rather than wages is the dominant adjustment mechanism to labor market shocks (see, e.g., Dustmann et al., 2016; Gathmann et al., 2020). Finally, we also demonstrate that men and medium-skilled workers benefited the most from the employment-stabilizing effect of digital investments.

A key concern of our estimation strategy is that firms that invested in digital technologies performed better even before the pandemic, were less negatively affected by the pandemic or had deeper financial pockets to absorb the negative effects of the pandemic than non-investors. We use a number of different strategies to address these concerns. All our specifications control for firm fixed effects to adjust for differences in the production technology or managerial ability. We further adjust for firm-specific linear trends to allow for differential trajectories in growing and shrinking firms or industries, for instance. Event studies comparing investing and non-investing firms show no differential pre-trends in employment or wage dynamics.

Firm fixed effects and firm-specific trends might not be enough to capture pre-existing differences in unobservable characteristics or developments that might affect investment decisions and wage or employment adjustments in the pandemic. We run a series of additional robustness checks focusing on specific samples to ensure that investing and non-investing firms are comparable. Splitting the sample into firms paying high and those paying low wage premia, we find a positive effect of digital investments in both sets of firms. The same result emerges for the sample of firms with deep pockets prior to the pandemic and those with low liquidity.

Another concern is that investing firms might have been more or less severely hit by demand disruptions during the pandemic than non-investing firms. Differences in pandemic exposure could then influence the decision to invest and employment or wage adjustments resulting in an omitted variable bias. We run three tests to address this concern. The first test adds state-specific year-by-month dummies to adjust for the different stringency of public containment measures imposed by federal states to limit the spread of the pandemic. The second test uses detailed industry-specific trends to control for differential shocks of trade or in the supply chain that affect some industries more than others. The results indicate that differences across regions and industries cannot explain the observed differential adjustments between investing and non-investing firms. Finally, investment has a positive effect on employment in firms hit hardest by the pandemic, while there is no relationship for firms that were hardly affected. These patterns support the view that the insurance effect of investments is not because investing firms were less affected economically by the pandemic.

Overall, the robustness checks show that the more favorable development of different employment outcomes of investing firms cannot be explained by investors having a better trajectory prior to the pandemic or facing less severe economic shocks or restrictions during the pandemic than non-investors. Instead, the robustness analysis corroborates our main results that it was indeed the investments in digital tools that accounted for the differential employment adjustments between investing and non-investing firms.

Our study contributes to several strands of the literature: studies on firm-level adoption of new technologies and its labor market consequences; the literature on the labor market impacts of the pandemic and studies on the role of short-time work schemes for absorbing aggregate economic shocks.

Existing evidence on firms' decision to innovate indicates that adopters of robots or automation technology are typically larger and more productive with a more skilled workforce than non-adopters (see Zolas et al. (2020); Acemoglu and Restrepo (2022) for the U.S.; Deng et al. (2020) for Germany; Aghion et al. (2020) for France; Koch et al. (2021) for Spain; Graetz and Michaels (2018) for OECD countries). We find a similar result for firms adopting digital technologies – despite the fact that robots automate production processes and are heavily concentrated in manufacturing, while the digital technologies we analyze are mostly used in white-collar jobs across a broad range of industries. Unlike previous studies, we analyze investment decisions in a severe health and economic crisis where uncertainty makes firms less willing to realize large investment projects (see also Babina et al., 2020).

We further contribute to studies on the labor market impacts of innovations like robots, automation technology more broadly and AI. Studies on the overall labor market effects of robots (Graetz and Michaels, 2018; Humlum, 2019; Acemoglu and Restrepo, 2020; Dauth et al., 2021; Koch et al., 2021; Benmelech and Zator, 2022) report mixed results. Some find few displacement effects, though there is a redistribution with job creation in adopting firms and job destruction in non-adopting firms (Koch et al., 2021); and job destruction in manufacturing but creation in services (Dauth et al., 2021; Gregory et al., 2022). Others find sizable displacement effects (Acemoglu and Restrepo, 2020; Bonfiglioli et al., 2020). There is yet very limited evidence on the influence of AI on the labor market pointing to modest positive to no effects (Acemoglu et al., 2022; Gathmann and Grimm, 2022; Babina et al., forthcoming). The most comprehensive analysis of firm-level innovation in technologies like cloud computing, online platforms, smart factories and robots also finds more stable employment and wage growth in adopting firms though the size of the effect depends on the technology adopted (Genz et al., 2021). We make four contributions here: we focus on digital tools rather than automation technologies; analyze the employment impact during a severe economic recession (see also Barth et al., 2022); provide evidence about the type of workers that benefited the most from the stabilization of employment relationships; and demonstrate that investments are complements to training.

Our study also adds to the literature on the consequences of the pandemic for labor demand, employment and wages (see, e.g., Adams-Prassl et al., 2020; Forsythe et al., 2020) and the studies showing the widespread use of remote work (Bloom et al., 2020; Dingel and Neiman, 2020; Alipour et al., 2021; Barrero et al., 2021; Kagerl and Starzetz, 2022). In particular, we show that digital technologies played an important part in how firms adjusted their employment to changing conditions. Moreover, our result that men benefit more from the stabilizing effect of investments is in line with the view of the pandemic as a 'she-cession', in which women have been hit disproportionately (Albanesi and Kim, 2021; Alon et al., 2022; Bluedorn et al., 2023). And while younger workers typically are hit most during recessions (Forsythe, 2021), we document that younger workers also benefit from digital investments of firms.

Finally, our analysis provides evidence on how labor market policies influence firm adjustments during an economic recession (Boeri and Bruecker, 2011; Giupponi and Landais, 2022). Many European countries relied on generous provisions for short-time work to avoid job displacements and help firms adjust to the pandemic situation (Giupponi et al., 2022).[3] The instrument had already been used extensively by governments in Europe during the financial crisis of 2008 (see, e.g., Kopp and Siegenthaler, 2021; Giupponi and Landais, 2022). While in the U.S. unemployment rose dramatically in the financial crisis and again in the pandemic, unemployment increased much less in countries with short-time work (OECD, 2021). Our evidence confirms that short-time work was an important instrument to reduce layoffs among the regular workforce. Moreover, short-time work together with digital investments was able to stabilize firm employment benefiting not only regular staff but also marginal workers who work much fewer hours and are not eligible for the short-time work scheme.

The paper proceeds as follows. The next section introduces the survey and matched administrative data on plants and their employees. Section 3 outlines our estimation strategies and discusses potential threats to identification. Section 4 presents empirical evidence on firm investments in digital technologies as well as training needs and activities in Germany. Section 5 shows the results of digital investments on employment, workforce composition and wages, reports several robustness checks and explores the heterogeneity of findings across firms. Section 6 discusses the results on employment flows and studies heterogeneities in worker types. Finally, Section 7 discusses the implications of our findings and concludes.

2 Data Sources

2.1 Establishment Survey

We make use of the novel survey "Establishments in the COVID-19 crisis", which was set up to analyze the impacts of the pandemic on establishments in Germany. The phone-based survey was designed as a rotating monthly panel and covered around 2,000 establishments per wave. Establishments were sampled from the universe of privately-owned establishments (with at least one employee who is subject to social

[3] In the German economy, short-time work stabilized employment levels of regular workers who are eligible for short-time work relative to marginal employees who are not (see Appendix Figure A.1).

security contributions) that are registered at the German Federal Employment Agency.[4] Specifically, firms were randomly drawn from strata consisting of broad sector $\times$ size cells. Large establishments with 250 or more employees are over-sampled to insure a sufficient number of observations. Each wave is representative of the private sector in Germany.[5] Further information on the survey and its design can be found in Bellmann et al. (2022) and Backhaus et al. (2022).

The information on investments in digital technologies and firm-provided training comes from the ninth wave, which was conducted in February 2021 and collected data on 1,941 establishments. As part of this survey wave, establishments reported whether they planned or realized investments in eight different types of digital technologies: hardware, software for collaboration, software for digital communication, remote access facilities, faster internet, data protection, recruitment of IT specialists or other digital investments.[6] For each type of technology, we also know whether or not the pandemic was the reason for the investment. In addition, we asked about firms' training needs in areas such as leadership or IT skills; and whether firms expanded or reduced their training activities during the pandemic. We also collected information on the current economic situation of the firm and how it was affected by the pandemic.

2.2 Linked Survey and Administrative Data

To analyze how investment in digital technologies affected firms' employment and wages, we link the survey to administrative data from social security records.[7] The administrative records are taken from the Integrated Employment Biographies (IEB), which cover the universe of all establishments with at least one employment spell that is subject to social security contributions.[8] We use monthly observations for each establishment from January 2018 to December 2020. The high frequency allows tracking the dynamics of employment outcomes and wages for investing and non-investing firms before and during the pandemic.

The administrative data contain detailed longitudinal information on the labor market biographies of all workers in the establishment. We know the type of the employment contract, i.e. whether an employee has a regular contract, works full-time or is marginally employed (earning up to 450 Euros per month). The type of employment is important because regular employees were eligible for short-time work during

[4]The public sector and extraterritorial organizations are excluded from the survey.

[5]and our results are robust to including survey weights. As bankruptcy regulation was eased during the pandemic, firm exits were at very low levels in 2020 (Müller, 2021) reducing concerns about selection bias during our sample period. Our results are robust to including survey weights.

[6]These types of technologies focus on office and communication tools and less so on production tools. Robots and other production-related technologies are not covered by the survey. Appendix A provides detailed information on the survey questions.

[7]More than 90% of the establishments surveyed in February 2021 agreed to have their survey responses matched.

[8]The data cover about 80% of the workforce in Germany. Self-employed workers, civil servants, and individuals doing military service are not included in the data set (see Oberschachtsiek et al., 2009).

the pandemic, while marginal employees were not. We also observe the number of workers leaving an establishment and the number of new employees at a monthly frequency. From the official accounts of the Federal Employment Agency, we obtain the number of workers in short-time work (STW) in each establishment in each month. In spring 2020, up to six million employees were in short-time work with a reduction of working hours of roughly 50% on average.

The administrative data further contain detailed worker characteristics like age, gender, skill and occupation. We aggregate a worker's occupation into four broad categories based on job requirements (Paulus and Matthes, 2013): unskilled and semi-skilled (requiring no formal training), specialist (requiring completed vocational training), complex specialist (requiring a master craftsman/technician status or a bachelor's degree) and highly complex occupations (requiring a college degree or more). We use these worker characteristics to adjust for compositional effects and explore which groups of workers benefit from investments in digital technologies. We further classify whether the occupation requires working with screens, which proxies how easy a job can be performed online and remotely (Matthes et al., 2023).[9]

We observe the average daily wage of each employee, which we use to construct firm-specific median wages. Observed wages from the administrative data are censored at the limit at which the maximum amount of social security contributions is paid. Our wage measure is the (log) median wage of a firm, which should be little affected by censoring. Furthermore, the data provide information about establishment wage premia measured by establishment fixed effects estimated from an AKM-style wage regression during the pre-pandemic period (2010-2017) (see Abowd et al., 1999; Bellmann et al., 2020b, for details). In addition, we characterize the industry of each establishment according to its knowledge intensity. In doing so, we distinguish between five broad groups: knowledge-intensive and non-knowledge-intensive manufacturing, knowledge-intensive and non-knowledge-intensive services and ICT industries (see Genz et al., 2019, for details). Finally, we merge information on population density and the share of the urban population of the establishment's location to define whether the local labor market is urban, semi-urban, semi-rural or rural. We use industry and local labor market controls to adjust for differences in the availability of and opportunity to use digital technologies.

[9]The proxy is constructed from information about whether screen work belongs to the tasks performed in the occupation.

3 Estimation Approach

3.1 Investment Decisions

We start by assessing the factors that influence an establishment's decision to invest in digital technologies. Specifically, we estimate variants of the following model:

$$DigInvest_f = \boldsymbol{\gamma_1}'\mathbf{X}_f + \varepsilon_{1f}, \tag{1}$$

where $DigInvest_f$ is an indicator that takes the value one if an establishment f has invested in *any* digital technology between March 2020 and February 2021, the peak period of the COVID-19 pandemic, and zero otherwise. The matrix $\mathbf{X}_f$ includes control variables at the establishment level, all measured in the pre-pandemic period (in 2019). Specifically, we control for the industry (characterized by its knowledge intensity and whether an establishment operates in manufacturing or the service sector), establishment size (*small* (less than 10 employees), *medium* (between 10 and 49 employees), *large* (between 50 and 199 employees) and *very large* establishments (200 or more employees)) and the firm wage premium to account for differences in production technology and and unobserved firm quality.

To adjust for differences in workforce composition, we control for the age distribution (*young* (less than 30 years), *prime-age* (between 30 and 50 years) and *older* (older than 50 years)), skill shares (*low-skilled* (no completed apprenticeship), *medium-skilled* (completed apprenticeship) and *high-skilled* (completed tertiary education)) and the occupational composition (based on job requirement as discussed in Section 2) in each establishment. We further include the share of regular and marginal workers, the share working full-time or part-time, the gender composition and the share of German and foreign citizens in the establishment. Finally, we control whether an establishment is located in East or West Germany and the degree of urbanisation of the local labor market.

In the next step, we investigate which particular digital technologies establishments invested in by using the following model:

$$DigInvest_f^d = \boldsymbol{\gamma_2}^{d'}\mathbf{X}_f + \varepsilon_{2f}^d, \tag{2}$$

where $DigInvest_f^d$ is an indicator that takes the value one if establishment f has invested in the digital technology of type d between March 2020 and February 2021, and zero otherwise. We distinguish between investments in hardware (e.g. laptops or cameras), software (e.g. for collaboration or communication) and supporting infrastructure (e.g. VPN or data protection). $\mathbf{X}_f$ includes the same set of establishment and workforce characteristics as Equation (1) above.

3.2 Training Needs and Training Activities

To study training needs and training activities at the establishment level, we estimate the following model:

$$Y_f = \beta_1 DigInvest_f + \boldsymbol{\gamma_3}'\mathbf{X}_f + \varepsilon_{3f}, \tag{3}$$

where Y_f is now an indicator equal to one if the establishment reports a training need or a training activity between March 2020 and February 2021, and zero otherwise. We distinguish between the following training needs: special IT knowledge (e.g. programming), skills in IT applications, skills in communication and cooperation, management skills, organisational skills and data protection skills. Similarly, we have information about the actual training activities the establishment undertook during the first year of the pandemic and whether this type of training has increased relative to the pre-pandemic period. The specification in Equation (3) further includes the indicator $DigInvest_f$, which is equal to one if the firm invested in digital technologies in the first year of the pandemic, and zero otherwise. The other control variables $\mathbf{X}_f$ are the same as before, all measured in the pre-pandemic year 2019.

3.3 Employment and Wages

To analyze labor market outcomes, we make use of monthly panel data from January 2018 until December 2020. In a first step, we analyze the dynamics of employment adjustments graphically by using an event-study-type framework. Specifically, we estimate the following model:

$$Y_{ft} = \sum_{m \neq Feb20} \beta_{2m}(DigInvest_f \times \mathbb{1}(t = m)) + \theta_f + \psi_t + \varepsilon_{4ft}, \tag{4}$$

where Y_{ft} now denotes firm-level outcomes like employment, the share of workers in short-time work, or the median wage of firm f in month t. The period of observations spans January 2018 to December 2020. $DigInvest_f$ is a time-constant indicator equal to one if an establishment invested in digital technologies, and zero otherwise. $\mathbb{1}(t = m)$ are monthly dummy variables and the coefficient β_{2m} captures the average difference in the outcome variable in month $t = m$ between investors and non-investors. ψ_t denotes fixed effects for each month to adjust for business-cycle fluctuations, the pandemic dynamic and other aggregate economic trends. θ_f are establishment fixed effects, which capture time-invariant firm-level heterogeneity.

In order to compare different specifications and to dig deeper into effect heterogeneity, we adjust Equation (4) in the next step, where we estimate variants of the following model:

$$Y_{ft} = \beta_3(DigInvest_f \times Post_t) + \theta_f + \psi_t + (\theta_f \times t) + \varepsilon_{5ft}, \tag{5}$$

where $Post_t$ is an indicator equal to one during the pandemic and zero for the time period before March 2020. This variable captures aggregate shifts in demand and supply that affect all plants equally during the pandemic. The interaction term $DigInvest_f \times Post_t$ is equal to one for investing firms during the pandemic, i.e. the period after February 2020. In addition to time and firm fixed effects, we include establishment-specific time trends $\theta_f \times t$ to capture differential employment trajectories or differential demand-side trends that are unobserved, but assumed to evolve linearly over time.

Our main parameters of interest are β_{2m} and β_3, which measure how investments in digital technologies are related to changes in labor market outcomes like employment or wages. The estimates reveal whether firms that invested in digital technologies have higher or lower employment growth than non-investing firms, for instance. The identifying assumption in Equation (4) and (5) is that firms that did not invest are a valid control group and would have experienced a similar employment or wage trajectory as investing firms in the absence of investments.

A key concern of our estimation strategy is that firms that invested in digital technologies have a better economic performance even before the pandemic, are less negatively affected by the pandemic or have deeper financial pockets to absorb the negative effects of the pandemic. We use a number of different strategies to address these concerns. All specifications control for firm fixed effects to adjust for unobserved heterogeneity across firms. We further control for detailed year-by-month dummies to capture the aggregate dynamic of the pandemic. To further adjust for differential trends across firms, we further include firm-specific linear trends in some specifications. To test for differential pre-trends between investing and non-investing firms, we use event studies for employment and wage dynamics, but fail to find any evidence for differences in pre-pandemic developments.

Firm fixed effects and firm-specific trends might not be enough to capture pre-existing unobservable differences that might affect investment decisions and wage or employment adjustments. We run a series of additional robustness checks to ensure that investing and non-investing firms are comparable. Specifically, we restrict the sample to high-performing firms, firms that report no financial constraints during the pandemic or firms with less severe demand disruptions. Neither of these sample restrictions affects our main results.

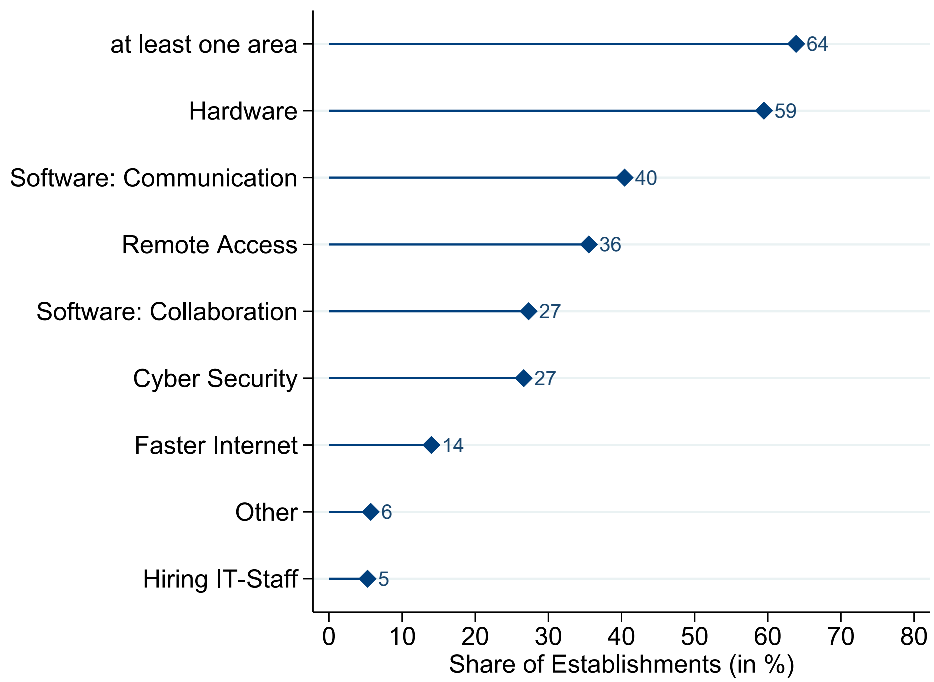
Another concern is that investing firms might have been more or less severely hit by demand disruptions during the pandemic than non-investing firms. Differences in pandemic exposure could then influence the decision to invest and employment or wage adjustments resulting in an omitted variable bias. We run two tests to address this concern. The first test adds state-specific year-by-month dummies to adjust for the different stringency of health measures to contain the pandemic. The second test uses detailed industry-specific trends to control for differential shocks like trade disruptions or supply chain issues that affect some industries more than others. The results indicate that differences across regions and industries cannot explain the observed differential adjustments between investing and non-investing firms. We report all robustness checks after our main results.

4 Empirical Evidence on Investments in Digital Technologies

4.1 The Pandemic as a Push Factor

Figure 1 provides descriptive evidence on he types of digital investments that firms invested in and whether this investment was made because of the pandemic or not. Almost two thirds of establishments invested in at least one digital technology during the first year of the pandemic. Establishments were most likely to invest in hardware (59%), followed by communication software like MS Teams or Zoom (40%), remote access (36%), software for collaboration like SharePoint or Google Docs (27%) as well as data protection and cyber security (27%). Interestingly, investments in improving internet speed or hiring additional IT-staff were much less common.[10] Many establishments undertook multiple investments; among investing firms, the median number of digital technologies invested in is three.

Figure 1: Investments in Digital Technologies



Notes: The figure shows the percentage of establishments undertaking investments in one of the specified digital technologies. $N = 1,814$ establishments.

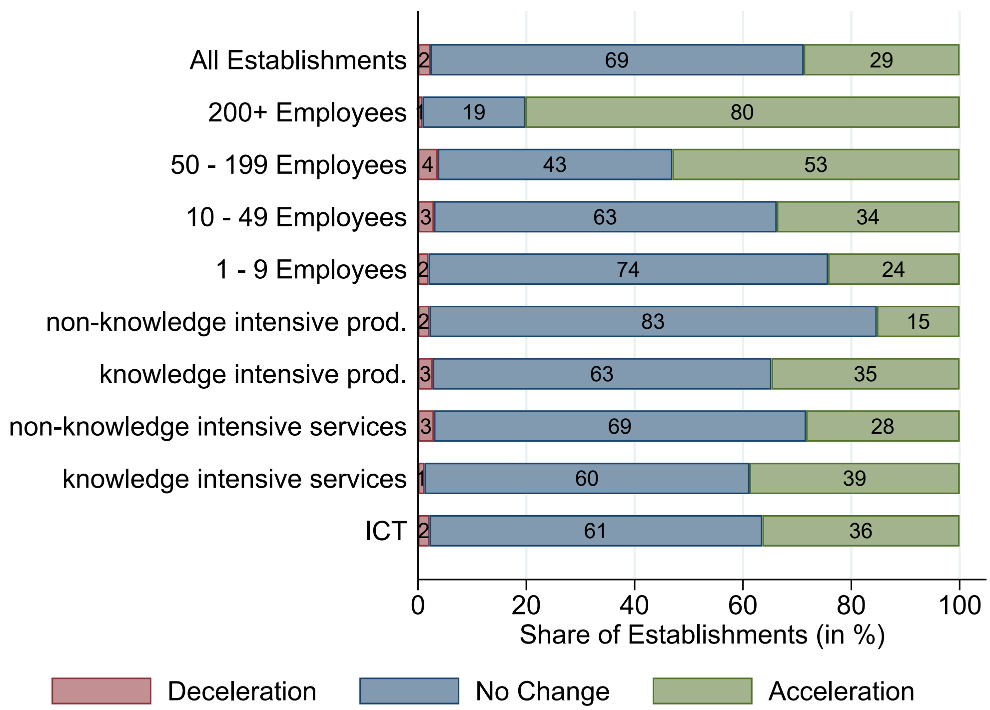
The overall numbers hide substantial heterogeneity across sectors. Establishments in knowledge-intensive and ICT industries were more likely to undertake investment in digital technologies than establishments in sectors such as construction that are not knowledge-intensive. Not all investments were necessar-

[10] Figure A.2 in the Appendix shows the share of investing firms for each digital technology as well as the share of firms that invested in this type of the technology because of the pandemic. For instance, the majority of firms that report to have invested in communication software did so because of the pandemic. By contrast, the pandemic is only reported by relatively few firms as the reason for investment in cyber security.

ily undertaken in response to the pandemic. Among the group of investors, roughly three quarters of establishments explicitly refer to the pandemic as the reason for investment.

Figure 2 shows how firms assess the pandemic's influence on the diffusion of digital technologies. Among all firms, 29% report that the pandemic has accelerated or expanded investments in digital technologies. In contrast, only very few establishments (2%) report that the pandemic slowed down the diffusion of digital technologies – despite the heightened uncertainty and difficulties to keep up business operations. Larger establishments are much more likely to report that the pandemic accelerated technological diffusion; 80% of the establishments with 200 or more employees view the pandemic as an important push factor. In contrast, only 24% of establishments with fewer than ten employees report that the pandemic accelerated digital investments. Firms operating in ICT or knowledge-intensive sectors are much more likely to view the pandemic as a push factor for the diffusion of digital technologies, while the share is lowest among firms in traditional manufacturing that is not knowledge-intensive.[11]

Figure 2: The Pandemic and the Adoption or Diffusion of Digital Technologies



Notes: The figure reports whether the pandemic has accelerated, decelerated or not affected the adoption or diffusion of digital technologies in the establishment. $N = 1,814$ establishments.

[11]Zooming in on industries, Appendix Figure A.3 reveals that firms in information and communications and other high-skilled services are most likely to report that the pandemic accelerated the diffusion of digital technologies followed by firms in wholesale and retail trade. The share is lowest for firms in agriculture, mining and energy as well as the hotel and food industry.

4.2 Who Invests in Digital Technologies?

So far, the evidence indicates that the pandemic accelerated investments in digital technologies in many establishments. Yet, who are the investing firms, how do they differ from non-investors and which firms invested because of the pandemic?

Investing firms are typically larger, pay higher wages as well as higher wage premia than non-investing firms. To some extent, these differences reflect that investing firms are more often active in knowledge-intensive sectors. Not surprisingly, investors and non-investors also differ in terms of the composition of their workforce. Investors have a higher share of skilled workers than non-investors (+6 percentage points), while the age and gender composition is similar. Investors also have a higher share of employees with regular contracts (+6 percentage points) and full-time workers (+7 percentage points). The differences in workforce composition indicate that establishments with a more productive workforce and whose workers are more strongly attached to the establishment (higher share of regular employees) are most likely to make additional investments in digital technologies. Appendix-Table A1 shows the full set of establishment and workforce characteristics separately for investors and non-investors.

One might expect that firms that invest because of the pandemic are ranked somewhere between all investing and non-investing firms. Yet, that is not the case. It is mostly large firms in knowledge-intensive industries with a highly skilled workforce, i.e. the technological leaders, that responded to the pandemic with additional investments in digital technologies.

To investigate the determinants of investments in digital technologies more systematically, we estimate logit models where the dependent variable is an indicator that takes the value one if an establishment invested in at least one digital technology, an zero otherwise. Table 1 reports average marginal effects based on the model in Equation (1) from Section 3 with the full set of observable firm and workforce control variables like firm size, industry, location and composition by age, skill, nationality and occupation.

Turning to a measure of overall firm quality, there is a weak positive correlation between higher wage premia and the propensity to invest in digital technologies, but the effect is not statistically significant in itself when adjusting for control variables such as firm size and sector. Moreover, the effect is economically small: a one standard deviation increase in the wage premium ($SD = 0.23$) is associated with an increase in the propensity to invest by at most 2 percentage points. Firms with a higher share of regular workers have a higher propensity to invest. Regular workers typically tend to be more attached to a firm and have longer tenure. In column (2), we add the share of employees working with computer screens. There is a positive association between screen work and investments in digital technologies – even conditional on the skill and occupational composition of the workforce and the sector of activity. Increasing the share of screen workers (which has a mean value of about 50%) by 10 percentage points is associated with an increase in the propensity to invest by 1.1 percentage points. Hence, investments in digital technologies are complementary to the observed shift to remote work observed in many countries during the pandemic (Barrero et al., 2021; Kagerl and Starzetz, 2022).

The remaining columns refer to those firms for whom the pandemic constituted the reason for investment in at least one area (columns (3) and (4)) and those for whom this was not the case (columns (5) and (6)). In both cases, the control group is the sample of non-investing firms. There is a small and statistically insignificant association between firm wage premia and investment propensities – irrespective of the reason for investment. The positive correlation between the share of regular workers and investments in digital technologies is explained by pandemic investors. This stronger impact likely reflects that firms have a higher willingness to invest if workers are more attached to the establishment. Similarly, the positive correlation between investments and the share of screen workers is also explained by pandemic investors, which indicates that digital investments were one tool to implement social distancing through remote work during the pandemic.

Table 1: Who Invests in Digital Technologies?

	Investment		Pandemic Investment		Independent Investment	
	(1)	(2)	(3)	(4)	(5)	(6)
Firm Wage Premium	0.070	0.054	0.088	0.069	0.057	0.051
	(0.055)	(0.055)	(0.062)	(0.062)	(0.079)	(0.080)
Share Regular Workers	0.132*	0.129*	0.196**	0.189**	0.077	0.076
	(0.078)	(0.079)	(0.087)	(0.087)	(0.110)	(0.110)
Share Screen Work		0.108**		0.155***		0.032
		(0.048)		(0.052)		(0.071)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Establishments	1530	1530	1269	1269	772	772

Notes: The table reports average marginal effects from logit regressions based on equation (1). In columns (1) and (2), the dependent variable is an indicator equal to one if an establishment has invested in digital technologies, and zero if not. In columns (3) and (4), the dependent variable is an indicator equal to one if an establishment has invested in digital technologies due to the pandemic, and zero if no investments were made. In columns (5) and (6), the dependent variable is an indicator equal to one if an establishment has invested in digital technologies independently of the pandemic, and zero if no investments were made. The firm wage premia (AKM fixed effects) are estimated for the period 2010 to 2017 (Bellmann et al., 2020b). AKM fixed effects are not available for newly established firms. Control variables are sector, firm size, a dummy for East Germany and degree of urbanization. Included workforce characteristics are shares of: occupational requirement levels (4 categories), age groups (3 categories), German nationality, women, full time workers, skill levels (3 categories). All workforce and establishment characteristics are measured in the pre-pandemic period (June 2019). Standard errors in brackets are clustered at the establishment level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Firms might also differ with respect to the types of digital technologies they invested in. It could well be that large firms with a good IT infrastructure mostly invested in online tools for communication, while smaller firms might had to invest in infrastructure like laptops or data protection first. Likewise, firms in manufacturing might have invested more in hardware and IT, while firms in the service industry might require more investments in cameras or communication tools. To analyze this question, we re-estimate Equation (2) from Section 3 where the dependent variables are now indicators for whether a firm invested in one of the eight digital technologies asked in the survey. Average marginal effects from logit models are reported in Appendix-Table A2. The share of regular workers is most strongly correlated with investments in hardware and online communication. In contrast, the share of screen work, which proxies for the potential of working remotely using digital technologies, is positively correlated with investments in hardware, software tools, remote access and internet speed. We generally find that larger firms and firms in knowledge-intensive sectors are more likely to invest in all types of digital tools. Conditional on firm and workforce characteristics, we find no association of firm wage premia with the probability of investment for any type of digital technologies.

Overall, investors are larger, have a more skilled workforce and pay higher wage premia. They are also more likely to operate in knowledge-intensive industries and services, where remote work was feasible with the support of digital technologies. The crisis thus seems to have increased the digital divide among firms: large firms and those operating in knowledge-intensive industries were more likely to respond to the pandemic's challenges through investments than smaller and medium-sized firms (see also Arntz et al., 2023, for evidence on the digital divide). Conditional on firm and workforce characteristics, we do not find that firms with higher wage premia, which might indicate more productive or better performing firms, are significantly more likely to invest in digital technologies.

4.3 Training Needs and Activities

Investments in hardware, software and IT infrastructure might not be enough to make use of digital technologies effectively. The workforce also needs to have the skills and competencies to use the new or upgraded tools in their daily work. Training might therefore represent an important complement to investments in digital tools. About 40% of firms report that their employees need to be trained in communication and cooperation skills; the share is even higher among large firms (66%). In addition, more than 30% indicate training needs in the area of data protection and cyber-security. To investigate training needs and actual training activities more systematically, we estimate variants of Equation (3) described in Section 3.

Table 2 reports estimates for six different skills related to digital technologies: traditional IT skills and IT programming skills (columns (1) and (2)), skills for online communication and cooperation as well as online management (columns (3) and (4)), planning and organizational skills and skills to ensure cyber security (columns (5) and (6)).[12]

Panel A of Table 2 shows the average marginal effects of any digital investment conditional on the full set of control variables. Establishments that invested in digital technologies have a substantially higher need for training in all six competencies, which underscores that training and investments in digital technologies are complements. The effects are strongest for communication and cooperation skills (+22 percentage points) followed by training needs in IT skills, management skills, planning and organization skills and cyber security skills (+15 to +17 percentage points). IT programming skills, in turn, are seen as less important (+10 percentage points).

Table 2: Investments in Digital Technologies and Training

	(1)	(2)	(3)	(4)	(5)	(6)
Training Need in...	IT Skills	Programming	Communic. & Cooperation	Management Skills	Planning & Organization	Cyber Security
			Panel A: Overall Investment			
Ref: No Investments						
Digital Investment	0.146***	0.101***	0.218***	0.148***	0.151***	0.172***
	(0.025)	(0.021)	(0.028)	(0.025)	(0.025)	(0.026)
			Panel B: Investment Reason			
Ref: No Investments						
Pandemic Investment	0.173***	0.118***	0.280***	0.187***	0.185***	0.213***
	(0.028)	(0.023)	(0.031)	(0.028)	(0.028)	(0.028)
Independent Investment	0.091***	0.062**	0.100***	0.059*	0.082**	0.084**
	(0.032)	(0.027)	(0.036)	(0.031)	(0.033)	(0.033)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Establishments	1526	1517	1523	1520	1522	1522
Mean Y	0.29	0.17	0.42	0.30	0.30	0.32

Notes: The table reports results from a multinomial logit model based on equation (3), where the dependent variable takes on three possible states: training need in the respective skill, no training need and skill not relevant in the firm. Shown are average marginal effects predicting the outcome 'has training need'. The row 'Mean Y' reports the share of establishments that indicate having a training need in the respective skill. The key independent variable in Panel A is whether an establishment invested in any digital technology; and zero if it did not invest. In Panel B, the key independent variables are two indicators: the first one is equal to one if the establishment invested in digital technologies because of the pandemic; and zero if it did not invest or would have invested independently of the pandemic. The second variable is an indicator equal to one if the establishment would have invested in digital technologies anyway; and zero if it did not invest or invested because of the pandemic. Control variables here are the same as in Table 1 (the share of regular workers, the screen work share and the establishment's AKM fixed effect are included). All control variables are measured in 2019. Standard errors clustered at the establishment level are reported in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In Panel B of Table 2, we compare the corresponding average marginal effects for firms that invested because of the pandemic and those for whom the pandemic was not the reason for investment. The reference group are again non-investing firms. Firms investing in response to the pandemic have a much

[12] As establishments could answer that a particular skill set is not relevant for their business, the table presents average marginal effects from a multinomial logit model (predicting the outcome of having a training need) where the dependent variable denotes whether a skill is not relevant for the firm, there is no training need or there is a training need.

higher training need for all skills than establishments that invested irrespective of the pandemic. The higher training need among pandemic investors is especially striking for management skills as well as communication and cooperation skills. Pandemic investors are about 28 percentage points more likely to have an elevated training need in cooperation and communication skills. In contrast, firms that invested independently of the pandemic have only a 10 percentage points higher training need than non-investing firms. Similarly, pandemic investors reported a 20 percentage points higher need for training in management skills compared to an increase of only 6 percentage points among independent investors.

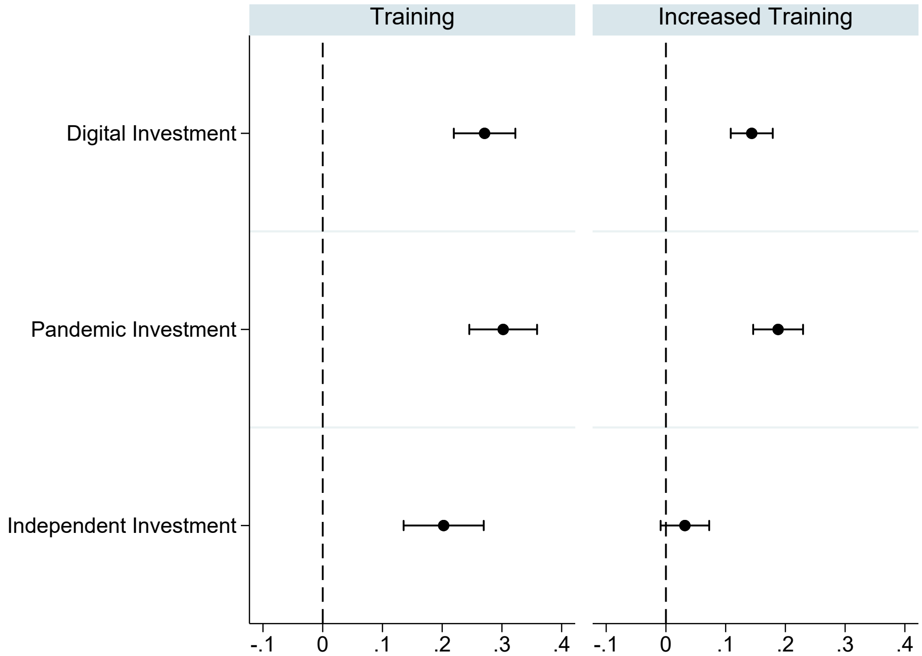
These results clearly show that the widespread and often unplanned adoption and diffusion of online meeting and communication tools within a short period generated a substantial need to upgrade worker skills, both in terms of hard and soft skills. Employers recognized that training is an important complement to the widespread investments in digital technologies in order to make productive use of the new tools.

Yet, did employers also act on the perceived need and offered more training to their staff? Or did they expect their workforce to train themselves through online courses or self-study instead? The answer is not obvious ex ante given that regular business activities were often disrupted or at least slowed down, personal contacts were difficult to organize and firms faced substantial uncertainty about the future. As a consequence, firms were severely limited, at least early on during the pandemic, in offering and holding training courses as planned because of contact restrictions or economic hardship (Bellmann et al., 2020a).

On average, 35% of establishments provided training courses in digital technologies and around 15% even increased their training efforts compared to the pre-pandemic period. Figure 3 presents the estimated coefficients obtained from regressing indicators of training activity on our investment and control variables according to Equation (3). In the left panel of Figure 3, the dependent variable is an indicator for whether any IT training took place between March 2020 and February 2021. Overall, establishments investing because of the pandemic are about 30 percentage points more likely to have carried out training courses than non-investing firms.

Moreover, firms that invested are also more likely to increase their training efforts during the pandemic. The right panel of Figure 3 shows whether firm-provided training *increased* during the pandemic relative to the pre-pandemic period. Investing firms are 15 percentage points more likely to have intensified training efforts during the pandemic than non-investing firms. These higher training efforts are almost entirely accounted for by establishments that invested in digital technologies because of the pandemic. For them, the propensity to intensify training increased by almost 20 percentage points compared to non-investing establishments. Establishments for whom the pandemic was not the reason for investing the probability of increased training is only 3 percentage point higher than non-investing firms, but this difference is not statistically significant.

Figure 3: Investment and Actual Training Activities



Notes: The figure shows average marginal effects and 95% confidence intervals obtained from regressions based on Equation (3). 'Digital Investment' is a dummy variable equal to one if the firm has invested in digital technologies in the pandemic. The investors are further split into the two groups 'Pandemic Investment' and 'Independent Investment', depending on whether they report that at least part of their investments were because of the pandemic or that they would have invested anyway in the absence of the pandemic. In the left panel, the dependent variable is a dummy variable indicating whether any IT-based training took place during the pandemic's first year. The right panel shows average marginal effects from multinomial logit regressions on whether an establishment has increased the amount of training during the pandemic's first year relative to the pre-pandemic period. The dependent variable can take on three states: Increased training relative to the year before the pandemic, reduced training, or unchanged level of training activities. Control variables here are the same as in Table 1 (the share of regular workers, the share working with screens and the establishment's AKM fixed effect are included). All control variables are measured in 2019. Standard errors are clustered at the establishment level.

Taken together, our results show a strong complementarity between investments in digital technologies, the need for workforce training and the actual provision of training by firms. Investors see considerably more training needs across a broad range of competencies related to digital tools. Most importantly, employers also acted on the perceived needs – despite the difficult circumstances – and raised their training efforts during the crisis.

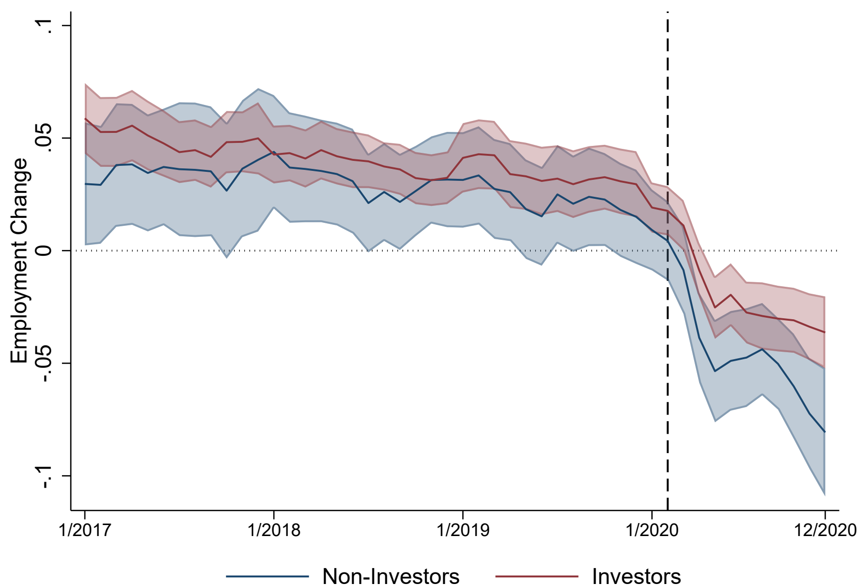
5 Digital Technologies and Employment Adjustments

We now turn to the question how firm investments in digital technologies influenced employment adjustments during the pandemic. To do so, we rely on monthly panel data at the firm level. We estimate variants of Equation (5) from Section 3 to provide systematic evidence on the effect of investments on employment adjustments. For a graphical representation and for assessing pre-trends in employment, we also use an event study framework (according to Equation (4) from Section 3).

5.1 Investments and Total Employment

Figure 4 shows unconditional changes in total (log) employment at monthly frequency. In the pre-pandemic period, investing and non-investing firms both experienced employment growth between 2 and 5% per year. When the pandemic started in March 2020, indicated by the vertical dashed line, employment plunged drastically in all firms. Figure 4 reveals that employment losses were less pronounced in investing firms and employment developed more favorably afterwards than in non-investing firms.

Figure 4: Changes in Total Employment

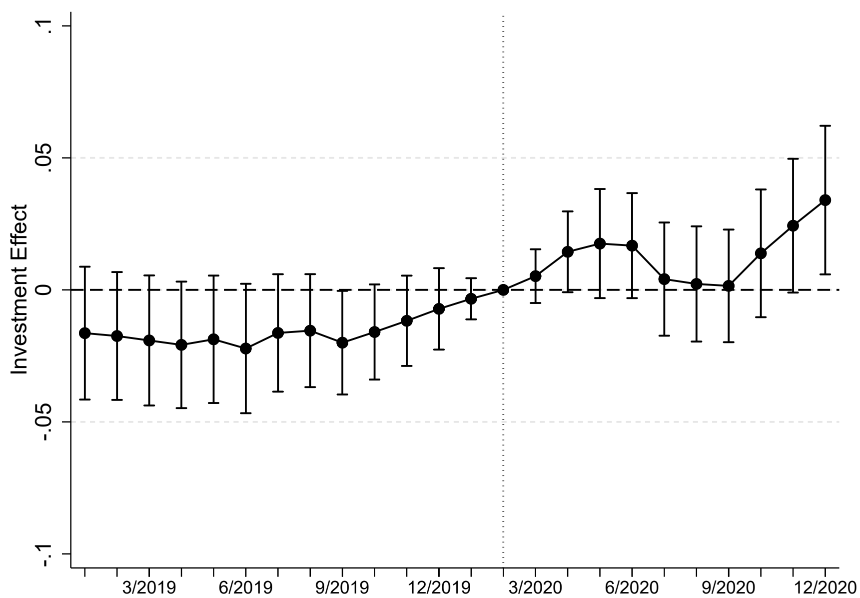


Notes: The graph shows the mean yearly change for total (log) employment separately for investors and non-investors and their respective confidence intervals (±2 SEs of the mean). The balanced sample consists of 1,711 firms that are observed in the administrative data over the whole period.

We next provide event study estimates for employment in investing and non-investing firms based on Equation (4). The estimates in Figure 5 confirm that there are no differences in the pre-pandemic development of employment between investing and non-investing firms. If anything, employment growth in investing firms was even slightly lower than in non-investing firms before the pandemic, though none of the pre-pandemic effects are statistically significant. After the onset of the pandemic, investing firms see smaller employment losses and a stronger recovery than firms that did not invest in digital technologies. The difference becomes statistically significant at the end of 2020.

Overall, Figure 5 shows that the more favorable development of employment in investing firms during the pandemic is not the result of investing firms being more successful and therefore growing more quickly compared to non-investors before investments are undertaken. The pattern supports our identifying assumption that investing and non-investing firms did not experience differential employment levels and trends prior to the pandemic.

Figure 5: Event Study Estimates for Total Employment



Notes: The graph shows the estimated β_2 coefficients and 95% confidence intervals from Equation (4) with total (log) employment as the dependent variable and controlling for time and firm fixed effects. The reference month is February 2020. Standard errors are clustered at the establishment level.

Table 3 shows the coefficient estimates of β_3 from Equation (5) for all firms as well as separately for firms that invested because of the pandemic and firms that invested independently of it. Column (1), which summarizes Figure 5 by comparing the average of the estimates until February 2020 with the average of the estimates from March 2020 onward, suggests that employment losses in the post-pandemic period were, on average, 3.4 percentage points lower among investors than non-investors. Distinguishing between pandemic and independent investors (in column (2)), we find similar effects, but the estimate is only statistically significant for pandemic investors.

Table 3: Investments in Digital Technologies and Total Employment

	(1)	(2)	(3)	(4)
Digital Investment	0.034***		0.010	
	(0.013)		(0.012)	
Pandemic Investment		0.035**		0.015
		(0.013)		(0.012)
Independent Investment		0.030		-0.003
		(0.020)		(0.019)
Firm FE	yes	yes	yes	yes
Time FE	year x month	year x month	year x month	year x month
Firm-specific Trends	no	no	yes	yes
No. Firms	1854	1854	1854	1854
Observations	65348	65348	65348	65348

Notes: The table shows the estimated β_3 coefficients based on equation (5). The dependent variable is total (log) employment. The key independent variables are whether an establishment has invested in digital technologies or not (columns (1) and (3)); or, whether an investing establishment has invested due to the pandemic or independently of it (in columns (2) and (4)). In all cases, the control group are establishments that did not invest. Columns (3) and (4) add firm-specific linear trends to capture unobserved differences in demand across firms. Standard errors in brackets are clustered at the establishment level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Though the visual evidence in Figure 5 does not indicate differential pre-trends, we next include establishment-specific trends. The estimates are now identified from deviations from a linear in firm employment. Column (3) and column (4) indicate that investors and non-investors exhibit only small and statistically insignificant differences (column (3)), which is concentrated among pandemic investors (column (4)). In sum, there is some evidence that investing firms suffer somewhat lower losses in total employment during the pandemic than non-investing firms.

5.2 Regular Employment, Marginal Employment and Short-Time Work

The inconclusive effect on total employment could mask substantial adjustments for different types of employment contracts. In what follows, we distinguish between regular and marginal employment. Regular employees are subject to social security contributions, while marginal employees, most of them in *Minijobs*, are not.[13] Hiring and firing marginal employees is considerably easier compared to regular employees because they are not covered by strict employment protection.

We further track whether regular employees work their regular hours or are in short-time work. Short-time work allowed firms to flexibly reduce their wage bill without laying off workers. In particular, establishments could reduce the labor costs of their regular employees where the earnings losses were partially compensated by the Federal Employment Agency. In principle, employers could reduce the working hours of regular employees to zero hours and employees received up to 87% of their previous earnings.[14] About six million employees, or one out of five regular employees (see Figure A.1 in the

[13]Individuals working in Minijobs cannot earn more than 450 EUR per month.

[14]This scheme was in place without restrictions between 2020 and 2022. Specifically, in the first four months, individuals

Appendix), were in short-time work in May 2020 and around one million workers continued to be covered by short-time work in August 2021. Workers in short-time work are still counted as part of regular employment even if they work fewer or zero hours. As such, employment records of the establishment do not capture this margin of adjustment. We therefore use administrative records on the number of employees in short-time work for each establishment and month.[15]

In response to the pandemic, firms may have adjusted their labor input in different ways: by laying off marginal workers who are less attached to the firm, by reducing the labor costs of their regular workforce through short-time work or through layoffs.[16] By providing generous compensation for regular employees, short-time work provides an attractive scheme for firms to smooth employment and thus delay or avoid layoffs among workers with substantial experience and firm-specific skills. We would therefore expect that firms mostly rely on short-time work to adjust their regular workforce.[17] Investments in digital technologies might help the establishment to keep their business running and reduce the need to fire workers or use short-time work schemes. Whether we see more layoffs of marginal workers or short-time work among regular employees depends on the relative productivity and labor costs during the pandemic.

Figure 6 shows raw changes of different types of employment for investing and non-investing firms. The top left panel shows the evolution of regular employment, where we observe few changes after the pandemic. The evolution shows little decline after the onset of the pandemic and also no differences between investing and non-investing firms. The top right panel traces changes in marginal employment. Before the pandemic, marginal employment evolves similarly in investing and non-investing firms. When the pandemic started, firms strongly reduced marginal employment and this decrease is much more pronounced for non-investors. Hence, non-investing firms laid off more of their marginal employees during the pandemic than investing firms. The bottom left panel shows the evolution of the share of regular employees in short-time work, which was mostly zero before the pandemic. With the start of the pandemic, short-time work jumps up in all firms – but short-time work is much more common in firms that did not invest in digital technologies. The panel shows a cyclical pattern where the difference in short-time work becomes smaller in late summer and fall 2020 before picking up again at the end of year. This pattern

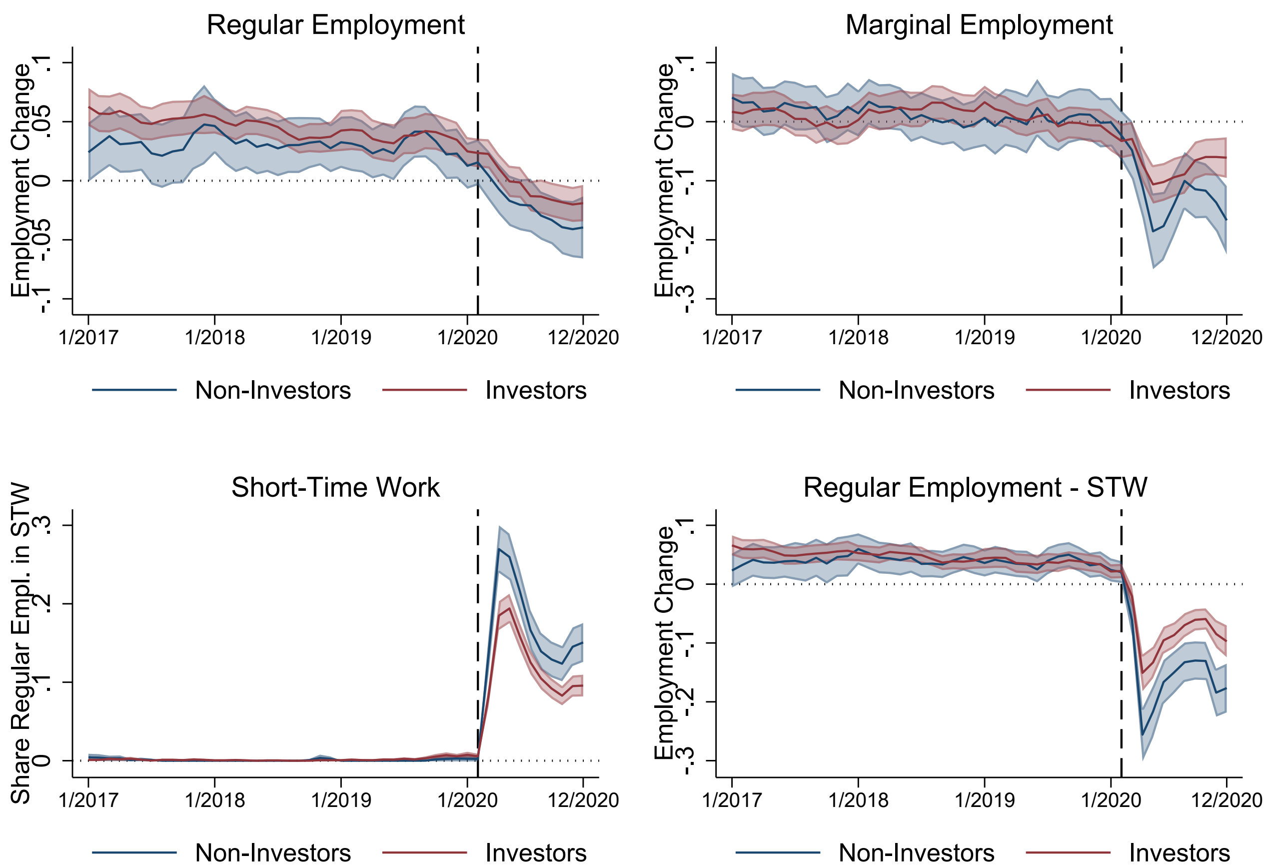
received 60% (67% for married individuals) of their prior earnings. The replacement ratio increased to 70% resp. 77% (80% resp. 87%) if a person was in short-time for four (seven) months or longer.

[15]Employers had to notify the Federal Employment Agency about the planned usage. The Federal Employment Agency closely monitored the actual usage of short-time work, which is why we have detailed administrative data available. We focus on the verified number of employees in short-time work at the establishment level for whom the Federal Employment Agency paid reimbursements.

[16]In addition to short-time work, firms can use other personnel policy measures to avoid layoffs and retain their staff. Firms can reduce the working hours of their employees even without short-time work, for example by no longer allowing working overtime or by reducing existing working time and vacation credits. Since our administrative data source does not include working time information, we cannot examine these adjustment channels in more detail.

[17]Also see Figure A.1 in the Appendix.

Figure 6: Employment Adjustments in Investing and Non-Investing Firms



Notes: The graph shows the evolution of regular employment, marginal employment, short-time work (STW) and regular employment minus STW separately for investors and non-investors as well as their respective confidence intervals (±2 SEs of the mean). Regular employment (shown in the top left panel) is subject to social security contributions and eligible for short-time work, while marginal employment (shown in the top right panel) is not. The bottom right panel shows regular employment net of STW, defined as the number of regular workers minus the employment equivalent in STW. The latter is calculated by multiplying for each firm the number of workers in STW with their average work loss. Mean annual changes are shown for regular employment, marginal employment and regular employment minus STW, while STW refers to the share of regular employees in STW. The sample consists of 1,711 firms that we observe in the administrative data over the whole period.

closely tracks the severity of the COVID-19 pandemic in Germany in terms of social distancing and lockdown measures. Finally, the bottom right panel tracks regular employees that were not on short-time work. The pre-pandemic evolution is very similar, largely because short-time work was not used much by firms then. From March 2020 onward, firms relied heavily on short-term work and the number of regular employees not in short-time work declines sharply. This change is however considerably more pronounced in non-investing firms.

To investigate the connection between investments in digital technologies and the different types of employment systematically, we re-estimate Equation (5) and Equation (4). Figure 7 plots event study estimates for the four employment categories (regular employees, marginal employees, short-time employees and regular employment not on short-time work) for investing firms relative to non-investing firms controlling for time and firm fixed effects. For regular workers not in short-time work (shown in the bottom right panel), there are a lot of zeros because many firms do not make use of short-time work in any given month; here, we use an inverse hyperbolic sine transformation.

Figure 7 shows clearly that during the pandemic investors in digital technologies fired fewer marginal employees, relied less on short-time work and kept more of their employees working regular hours than firms that did not invest in digital technologies. Investors have a 5 to 8 percentage points lower share of workers in short-time work. Accordingly, investing firms keep a higher share of their employment working regular hours than non-investing firms.[18] Investing firms were thus much better able to insure their workforce from the economic shocks of the pandemic. The insurance effect applies to both marginal workers, for whom we see fewer layoffs, as well as to regular employees, who are less likely to work reduced hours.

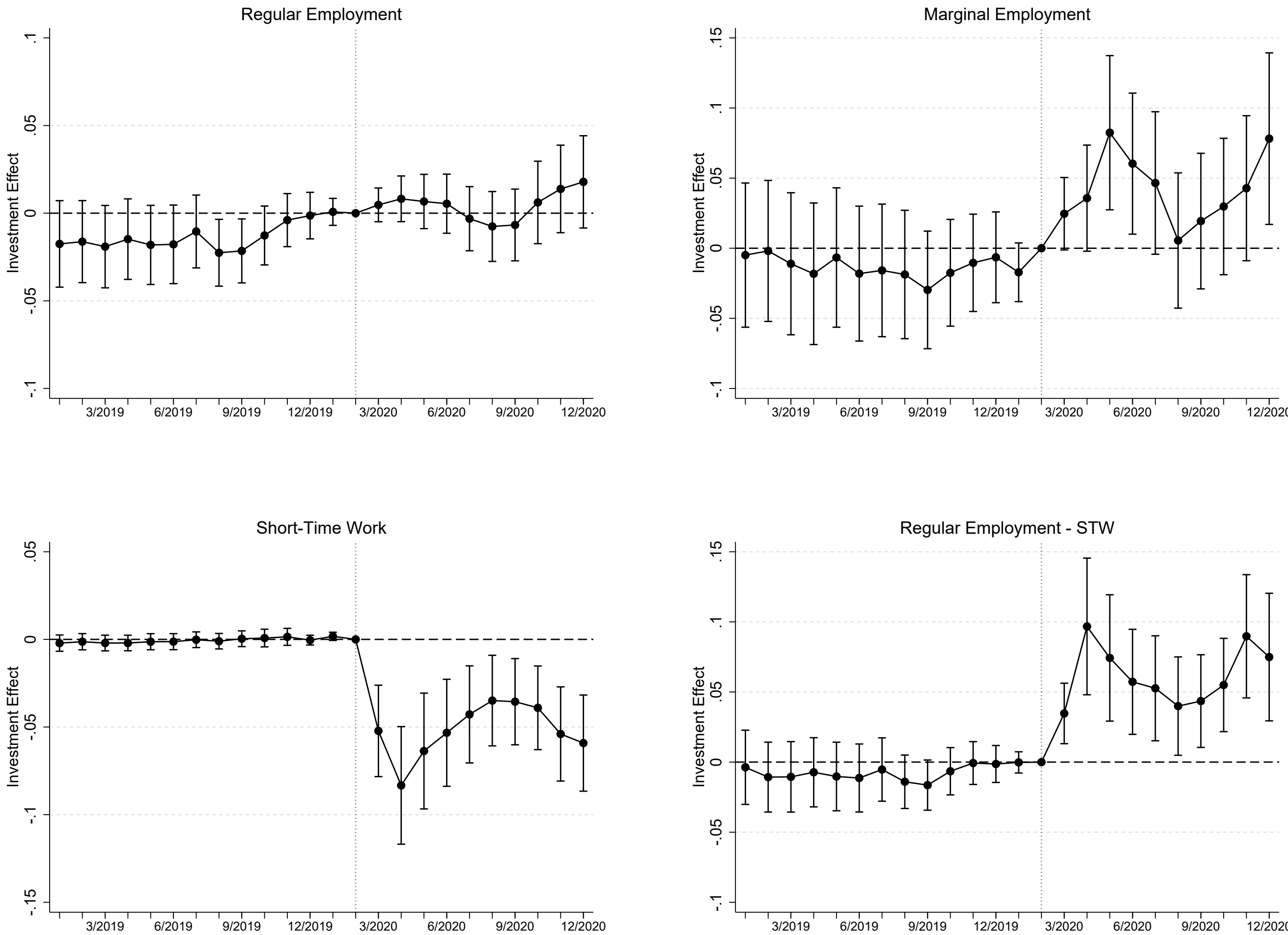
The estimated relationships are summarized in Table 4. We first compare employment adjustments for different types of workers in investing firms and non-investing firms. In even columns, we split investing firms into firms that invested because of the pandemic and firms did not invest because of the pandemic. In addition to time and firm fixed effects and motivated by the findings from Table 3, we also include firm-specific linear time trends.

The first two columns of Table 4 show that investing firms, irrespective of the investment reason, did not increase or reduce regular employment compared to non-investing firms (columns (1) and (2)). If we zoom in on the share of regular employees in short-time work (column (3)), we find investors to have a share that is five percentage points lower. Considering the employment equivalent not in short-time work in column (5), we find that the change in this quantity between the pre-pandemic and the pandemic period is about 6 percentage points larger in investing than in non-investing firms, confirming the more favourable development of investors in Figure 7.[19] Column (6) shows that this effect is primarily due to firms that invested *because* of the pandemic. Column (7) shows that a similarly sized and statistically significant positive effect can be found for marginal employees in investing firms. Here, however, the

[18]Note that this measure of short-time work combines changes in short-time work (the numerator) with changes in regular employment in general (the denominator).

[19]We also use an alternative definition of regular employees not in short-time work by calculating the difference between regular employment and the number of workers in short-time work (rather than the employment equivalent). The effect of investments on this alternative measure of employment working regular hours is roughly twice as large, which makes sense as the average number of hours lost due to short-time work in the pandemic was about 50%.

Figure 7: Event Studies for Different Types of Employment



Notes: The graph shows the estimated β_2 coefficients and 95% confidence intervals from Equation (4) controlling for time and firm fixed effects. For regular and marginal employment, the dependent variable is total (log) employment. For short-time work (STW), the dependent variable is the share of regular employees in short-time work. For regular employment net of short-time work the inverse hyperbolic sine is used. The reference month is February 2020. Standard errors are clustered at the establishment level.

effect is of similar size for firms for whom the pandemic represents the reason for investment and those for whom this is not the case.

5.3 Robustness Checks

We perform a range of robustness checks to ensure that the differential employment performance of investing and non-ivesting firms during the pandemic is not the result of pre-existing characteristics or trends. Table 5 reports a variety of alternative specifications for regular and marginal employment. To ease comparison, we display the estimates from the baseline model in column (1). Recall that our baseline specification contains both firm fixed effects and firm-specific linear trends to account for time-invariant

Table 4: Investments and Different Employment Margins

	Regular Employment (1)	(2)	Share in STW (3)	(4)	Regular Employment − STW (5)	(6)	Marginal Employment (7)	(8)
Digital Investment	0.001		-0.054***		0.057***		0.056**	
	(0.011)		(0.012)		(0.018)		(0.026)	
Pandemic Investment		0.002		-0.052***		0.064***		0.051**
		(0.011)		(0.013)		(0.019)		(0.027)
Independent Investment		-0.003		-0.059***		0.039		0.070**
		(0.018)		(0.016)		(0.027)		(0.034)
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes	yes	yes
Firm-specific Trends	yes	yes	yes	yes	yes	yes	yes	yes
No. Firms	1854	1854	1854	1854	1854	1854	1665	1665
Observations	65348	65348	65348	65348	65348	65348	53021	53021

Notes: The table shows the estimated β_3 coefficients based on equation (5). The dependent variables are (log) regular employment in columns (1) and (2), the share of regular employees in short-time work in columns (3) and (4), regular employment minus the employment equivalent in short-time work (using the inverse hyperbolic sine transformation) in columns (5) and (6), and (log) marginal employment in columns (7) and (8). Odd columns show the results for the whole sample comparing investing and non-investing firms. Even columns further distinguish between firms investing because of the pandemic and firms investing independently of it. The control group are non-investing firms. All specifications include time (year x month) and firm effects as well as firm-specific linear trends. The number of firms is lower for marginal employment as not all firms make use of that type of employment. Standard errors are reported in brackets and are clustered at the establishment level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

factors such as firms' labor intensity as well as different trajectories between growing and shrinking firms or industries, for instance.

One concern is that some firms might have been exposed to more severe economic restrictions during the pandemic as health measures were decided at the state level. To adjust for such state-specific shocks, we add year $\times$ month $\times$ state fixed effects to the specification. Adjusting for regional shocks has few effects on our estimates, however. Rather than regional shocks, industries were affected very differently by the pandemic depending on whether they were affected by contact restrictions, problems in their supply chains or were part of the critical infrastructure. To control for differential industry-specific shocks, we control for year $\times$ month $\times$ industry fixed effects in column (3).[20] The results remain unchanged. Alternatively, column (4) includes year $\times$ month $\times$ 2-digit industry fixed effects. The central finding that investors within the same industry have more favorable employment developments than non-investors during the pandemic is again unaffected.

An alternative way to check for differences in the pandemic-related economic conditions is to use information reported by firms in the survey. Specifically, we distinguish between firms that reported (very or moderately) negative effects and firms that reported no negative effects in spring 2020. Column (5) in Table 5 shows the results for the sample of firms reporting negative effects, while column (6) contains results for the sample of firms reporting no negative effects. In these specifications, we also control for year $\times$ month $\times$ industry fixed effects to account for the differential severity of shocks that

[20]Industries are defined by 19 broad categories, see Section 2.

industries experienced during the pandemic. The results show that among firms that were (strongly or somewhat) negatively affected by the pandemic, investors were significantly less likely to make use of short-time work and experienced a more favorable development of regular employment (net of short-time work). The effect on marginal employment is of a similar magnitude as in the baseline specification, but no longer statistically significant. By contrast, we find no evidence that investment favorably affected the development of regular employment or the extent of short-time work among firms that were not hit by the pandemic. In terms of the use of short-time work, this is to be expected as being negatively affected by the pandemic is a condition for being eligible for this support scheme. The estimated coefficient of the investment indicator on marginal employment is similar in terms of magnitude to the effect in the baseline model (column (1)), but not statistically significant. The evidence from columns (2) to (6) confirms that neither industry-specific shocks, nor differences in the economic shock experienced by firms nor differential pandemic measures can explain the result that firms who invested in digital technologies have more favorable employment outcomes during the pandemic.

Another concern is that investing firms have more favorable employment trajectories than non-investors because they have better financial resources or are otherwise more capable to compensate adverse shocks of the pandemic without laying off workers. To check this, we restrict the sample to firms in the top half of the AKM firm fixed effects distribution. Column (7) shows that even among high-quality firms (as measured through AKM firm FE), investors are less likely to make use of short-term work schemes and are more likely to retain regular and marginal employees. Results for lower-performing establishments, shown in column (8), are similar, though less precise.

Alternatively, we use survey information on the financial resources the firm has available to check whether investing firms performed better not because of the digital technologies, but because they had deeper pockets than non-investors to cushion the adverse economic effects of the pandemic. Column (9) of Table 5 restricts the sample to firms that reported in February 2021 having sufficient financial funds to keep their operations running even if the situation in early 2021 would continue. We would expect that firms in that sample did not face severe liquidity constraints, which could have inhibited any investment activities or constrain their operations in other ways. Again, the share of investing firms is somewhat higher in the sample of firms reporting no liquidity constraints. Yet, even if we restrict the sample to financially liquid firms, we still – also comparing it to column (10) – find that investing firms have more favorable employment outcomes than non-investing firms. These additional tests provide support for the view that the investment in digital technologies are responsible for the better employment outcomes during the pandemic and not the prior performance or financial situation of firms.

Table 5: Robustness Checks

	(1) Baseline	(2) Region x Time FE	(3) Industry x Time FE	(4) 2-digit Ind. x Time FE	(5) Negative Effects	(6) No Negative Effects	(7) Top Half Firm FE	(8) Bottom Half Firm FE	(9) High Liquidity	(10) Low Liquidity
Panel A: Regular Employees in Short-Time Work										
Digital Investment	-0.054***	-0.056***	-0.051***	-0.052***	-0.086***	0.003	-0.045***	-0.044*	-0.029**	-0.053***
	(0.012)	(0.012)	(0.012)	(0.011)	(0.018)	(0.007)	(0.016)	(0.023)	(0.014)	(0.017)
No. Firms	1854	1854	1854	1854	1002	850	1022	512	876	978
Panel B: Regular Employment − Short-Time Work										
Digital Investment	0.057***	0.061***	0.052***	0.048***	0.079***	0.008	0.040*	0.063	0.042**	0.042
	(0.018)	(0.018)	(0.017)	(0.017)	(0.026)	(0.018)	(0.022)	(0.038)	(0.021)	(0.026)
No. Firms	1854	1854	1854	1854	1002	850	1022	512	876	978
Panel C: Marginal Employment										
Digital Investment	0.056**	0.056**	0.053**	0.060**	0.046	0.048	0.074*	0.046	0.075**	0.035
	(0.026)	(0.026)	(0.026)	(0.027)	(0.037)	(0.034)	(0.039)	(0.047)	(0.037)	(0.035)
No. Firms	1665	1665	1665	1665	902	761	946	459	790	874

Notes: The table shows the estimated β_3 coefficients based on equation (5), where all specifications include firm fixed effects, time (year $\times$ month) fixed effects and firm-specific time trends. In column (2), the time fixed effects are interacted with federal states. In columns (3) and (4), the time fixed effects are interacted with broad industries and detailed two-digit industries, respectively. Column (5) shows results for the sample of firms reporting moderate or severe negative effects at the start of the pandemic; column (6) for the sample of firms reporting few or no adverse effects at the start of the pandemic. Specifications in columns (5) and (6) further include year $\times$ month $\times$ broad industry fixed effects. In columns (7) and (8), the sample is restricted to firms in the top half and bottom half of firm fixed effects, respectively. Finally, columns (9) and (10) restrict the sample to firms that report facing no liquidity constraints and some liquidity constraints, respectively. Again, the specifications in these two last columns control for year $\times$ month $\times$ broad industry fixed effects. Standard errors reported in brackets are clustered at the establishment level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Overall, the robustness checks show that the more favorable development of different employment outcomes among investing firms cannot be explained by investors facing less severe economic shocks or restrictions during the pandemic than non-investors. Moreover, we find a very similar impact of investments on employment if we focus on high-performing firms or firms with better financial resources. All results confirm that investors in digital technologies were better able to insure their workforce against the adverse effects during the pandemic.

5.4 Heterogeneity across firms

We next ask whether the observed employment adjustments differ across firms depending on their investment intensity, their training activities, their main sector or their size. Table 6 reports results from our baseline specification for the share of employees in short-time work (Panel A), the number of regular employees net of those in short-time work schemes (Panel B) and marginal employment (Panel C).

We first split the sample into moderate investors (firms with three or less investments in digital tools) and heavy investors (firms investing in more than three digital tools). Non-investors remain the control group in each case.[21] We find that all investors, independent of their scope of investments, sent fewer of their regular workforce into short-time work relative to non-investing firms. However, firms that invested more heavily into digital tools had more regular employees not on short-time and reduced marginal employment by less than moderate investors.

Moreover, Section 4.3 demonstrated that training needs and activities are strong complements to investments in digital technologies. One would expect that firms that invest into their workforce even during an economic downturn are able to retain their workforce and keep up operations better than firms with low or no training activities. Columns (3) and (4) split the sample into firms that undertook training activities during the pandemic and those that did not with all non-investing firms constituting the control group. Firms that undertook training activities send fewer workers into short-time work compared to non-investors and relative to firms with no training activities. Correspondingly, regular employees are more likely to work normal hours and marginal employment declines by less if the firm trained their workforce in how to use digital tools.

Given the nature of the pandemic, we would also expect that investments in digital technologies might have different effects in manufacturing versus services. In high-skilled services like finance, communications or consulting, for instance, digital tools are a powerful tool to maintain operations. In low-skilled services, digital tools can often not replace face-to-face interactions as business closures required employment

[21] Descriptive results from Section 4.1 indicate that the median establishment invested in three digital tools. We use the investment scope to proxy for how strongly investing firms adjusted their workflow during the pandemic.

Table 6: Heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	≤ 3 Inv. Areas	> 3 Inv. Areas	Training	No Training	Manufacturing	Services	<50 employees	≥ 50 employees
				Panel A: Share Regular Employees in Short-Time Work				
Digital Investment	-0.052***	-0.056***	-0.061***	-0.046***	-0.009	-0.070***	-0.038**	-0.090***
	(0.014)	(0.014)	(0.013)	(0.014)	(0.019)	(0.015)	(0.016)	(0.023)
No. Firms	1303	1226	1254	1269	515	1294	1083	764
				Panel B: Regular Employment − Short-Time Work				
Digital Investment	0.038*	0.079***	0.085***	0.029	0.043*	0.054**	0.040*	0.102***
	(0.022)	(0.019)	(0.019)	(0.022)	(0.022)	(0.023)	(0.023)	(0.038)
No. Firms	1303	1226	1254	1269	515	1294	1083	764
				Panel C: Marginal Employment				
Digital Investment	0.038	0.077***	0.071**	0.041	0.027	0.066**	0.023	0.209***
	(0.029)	(0.029)	(0.028)	(0.029)	(0.045)	(0.032)	(0.029)	(0.057)
No. Firms	1147	1087	1111	1118	461	1167	919	743

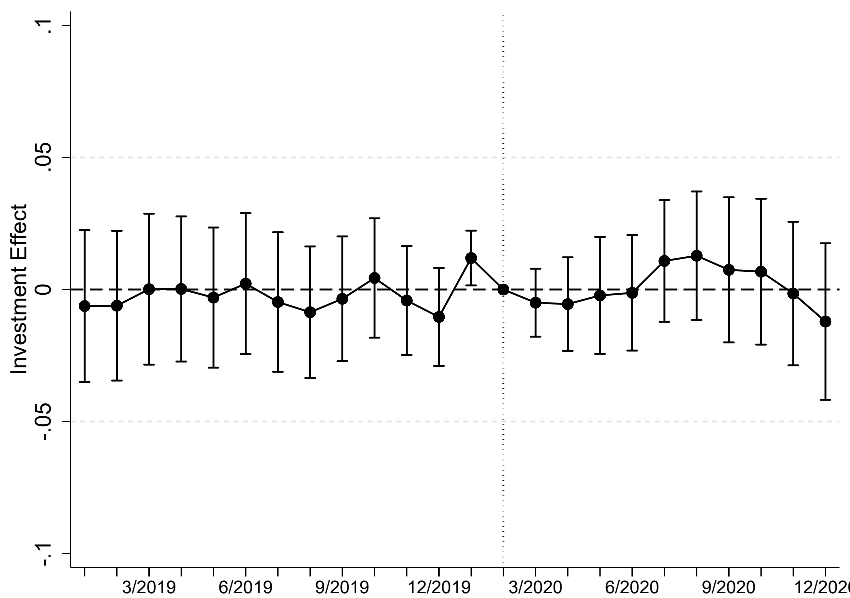
Notes: The table shows the estimated β_3 coefficients based on equation (5), where the dependent variables are the share of regular employees in short-time work in Panel A, the regular employees not in short-time work (using inverse hyperbolic sine to account for the large number of zeros) in Panel B, and log marginal employment in Panel C. All specifications include firm fixed effects, time (year $\times$ month) fixed effects and firm-specific time trends. Columns (1) and (2) split the sample according to the median number of digital tools a firm invested in. Columns (3) and (4) split the sample according to whether the firm engaged in training activities or not during the first year of the pandemic. The control group in columns (1)-(4) are all non-investing firms. Columns (5) and (6) split the sample into firms operating in manufacturing and service sector respectively. Here, we include year $\times$ month $\times$ broad industry fixed effects as well. Columns (7) and (8) split the sample by establishment size in February 2020, with 50 being the threshold for the total number of employees. Standard errors reported in brackets are clustered at the firm level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

reductions in any case. Yet, digital tools might assist in adjusting to business closures by setting up an online shop or introducing payments by card rather than cash, for instance. In manufacturing, digital tools might assist production and management but other disruptions, especially in supply chains or international trade, could counteract this effect in that sector. Columns (5) and (6) split the sample into firms in manufacturing and the service sector. To control for industry-specific shocks, we also include year-by-month-by-broad industry fixed effects. The results show that investments in digital tools matter more in the service sector. Investors in the service sector rely much less on short-time work and reduce marginal employment less than non-investors in services. It is thus particularly firms in the service sector where digital tools helped to protect the workforce and vulnerable marginal employees from the severe shock of the pandemic. Lastly, columns (7) and (8) split the firms by size, with 50 employees being the threshold. For both small and large firms, the coefficients consistently show the same sign, but the relationships we find are considerably stronger when comparing larger firms (50 employees or more) with each other, particularly in the case of marginal employment.

5.5 Wages

Rather than changing employment levels during the crisis, firms may have adjusted wages of workers instead. To test for wage adjustments, Figure 8 shows the event study plot for median wages of full-time employees in an establishment. The figure provides further support for our identifying assumption that investing firms did not have more favorable wage growth prior to the pandemic. Moreover, there is little evidence that investing firms adjusted wages differently in response to declining demand or disruptions in production compared to non-investing firms. We use our baseline specification in Equation (5) with the (log) median wage of full-time employees in a firm as the dependent variable. The estimate for investing firms versus non-investing firms is $\hat{\beta}_3 = -0.007$ with a standard error of 0.012. As Table 4 indicates changes in the composition of the workforce, we also re-estimate the specification controlling for workforce composition; we still find no wage effect. Hence, investing firms did not adjust wages differently than non-investing firms.

Figure 8: Event Study Estimates for Wages



Notes: The graph shows the estimated β_2 coefficients and 95% confidence intervals from Equation (4) with (log) median wages as the dependent variable and controlling for time and firm fixed effects. The reference month is February 2020. Standard errors are clustered at the establishment level.

In an economy where adjusting wages is not feasible, firms might postpone wage increases instead. We use information on planned wage increases from an earlier wave that was conducted in January 2021. About 30% of investing firms and an equal share of non-investing firms reported that they had indeed postponed wage increases.[22]

In sum, despite the sizable disruptions of the pandemic, we find few adjustments in wages through either wage cuts or differential wage growth between investing and non-investing firms. The absence of a wage effect indicates substantial downward wage rigidity in the German labor market. This finding is in line with other studies that find few effects on wages after mass layoffs or immigration in Germany (Gathmann et al., 2020; Dustmann et al., 2016).

6 Employment Flows and Worker Heterogeneity

6.1 Employment Flows

We have shown that employment dynamics during the pandemic differed substantially between firms with and without investments after the start of the pandemic. Figure 6 showed that all firms reduced employment during the pandemic with a stronger decline and a weaker rebound among firms that did not invest in digital technologies. In principle, such downward adjustments could occur either by hiring fewer workers, by firing more workers or by increasing the share of workers on short-time work. Likewise, the employment recovery could be driven by hiring more workers, by reducing short-time work or by reducing firm turnover. To better understand how investors and non-investors adjusted their workforce, we study monthly inflows and outflows as well as net inflows at the firm level based on Equation (5). As before, we use an inverse hyperbolic sine transformation to account for the large number of firms with zero inflows, outflows or netflows.

Results are shown in Table 7. Total employment flows in Panel A reveal that inflows declined more among investing firms, though the coefficient is only weakly statistically significant. More importantly, outflows from investing firms are significantly lower than from non-investing firms. The lower outflows in column (2) of Panel A support the view that investments in digital technologies helped firms keep up production and thereby retain more of their workforce during the pandemic. As a result, firm retention as measured by netflows in column (3) is positive in investing firms, which is in line with the more positive employment prospects documented in the previous section.

Panel B and C study inflows and outflows among regular and marginal employees, respectively.[23] In Panel B, we find a very similar pattern as for total employment. Investing firms had smaller inflows of regular employees than non-investing firms. At the same time, outflows of regular employees were much

[22] Here, the sample consists of about 900 firms that were part of the January 2021 *and* the February 2021 waves.

[23] Information on short-time work is available at the firm level, but not for the individual employee. Hence, we cannot study inflows and outflows for employees in short-time work. However, this does not limit our analysis as short-time workers cannot be easily fired and it seems highly unlikely that a recent hire would immediately be put on short-time work.

lower among investing firms than among non-investing firms. As a result, investing firms saw less turnover among regular employees than non-investing firms. The results for marginal employees in Panel C suggest that inflows of marginal workers were relatively similar between investing and non-investing firms, while investing firms still had lower outflows among their marginal employees than non-investing firms. The netflows in column (3) corroborate the finding that investors retained more marginal employees during the pandemic.

Table 7: Investments in Digital Technologies and Employment Flows

	(1) **Inflows**	(2) **Outflows**	(3) **Netflows**
		Panel A: Total Employment	
Digital Investment	-0.039*	-0.081***	0.061**
	(0.020)	(0.017)	(0.029)
		Panel B: Regular Employment	
Digital Investment	-0.048***	-0.074***	0.030
	(0.018)	(0.015)	(0.025)
		Panel C: Marginal Employment	
Digital Investment	0.013	-0.023**	0.046***
	(0.013)	(0.010)	(0.017)
No. Firms	1854	1854	1854
Observations	63479	63479	63479

Notes: The table shows the estimated β_3 coefficients based on equation (5), where all specifications include firm fixed effects, time (year $\times$ month) fixed effects and firm-specific time trends. Column (1) studies monthly inflows at the firm level, column (2) monthly outflows and column (3) monthly netflows defined as inflows minus outflows as dependent variables. Each dependent variable is transformed with the inverse hyperbolic sine to account for the large number of zeros in the flows. Panel A reports results for total firm employment flows, Panel B for flows among regular employees and Panel C for flows of marginal employees. Inflows refer to the month a person starts working for a firm and outflows refer to the last month a person worked at a firm. To calculate netflows, we use inflows in month t and outflows in month $t-1$. Standard errors reported in brackets are clustered at the establishment level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

6.2 Which Workers Benefit from Investments in Digital Technologies?

The higher retention rate of employees in investing firms might benefit some workers more than others. Overall, firms might be more eager to keep their skilled and experienced workforce to preserve their human capital during the pandemic. However, we have shown that regular employees could be insured through short-time work, whereas marginal employees who tend to be lower skilled could not be. How investments affect the decision who to retain, who not to hire or who to layoff is not clear ex ante.

We thus analyze worker inflows, outflows and netflows for different skill groups, age groups and by gender. The results based on our baseline specification (5) are shown in Table 8. Panel A distinguishes between low-, medium- and high-skilled workers; Panel B reports results for young workers below age 30, prime-aged workers between the age of 30 and 50 and older workers above age 50; and Panel C reports results for men and women.

According to the results in P, investing firmanel As are slightly less likely to hire high-skilled workers than non-investing firms (column (1)). Turning to outflows in column (2), we see that investing firms have fewer outflows across all skill groups. Yet, investing firms retain a much larger share of medium-skilled workers than non-investing firms. Medium-skilled workers are those with vocational training and most likely to have human capital that is specific to the firm. Overall, all skill groups seem to benefit from the digital investments through higher retention, but the insurance effect is larger for medium-skilled workers. The netflows in column (3) being most significant for the low-skilled is not surprising since we see the strongest employment effects for marginal employees (see Table 4 above), who are generally on the lower end of the skill spectrum.

Panel B shows that investing firms and non-investing firms do not differ in their recruitment intensity with respect to age groups. Yet, outflows of young and prime-aged workers are substantially lower resulting in a higher retention rate among investing firms. Hence, it is mostly workers under the age of 50 that benefit from the insurance effect of digital investments. Finally, Panel C shows that men benefit more from digital investments than women. As before, the adjustment mostly occurs through reduced outflows among investing firms rather than more recruitment.

7 Conclusion

The COVID-19 pandemic has forced firms to adapt their work processes to the pandemic situation and the public health measures to contain it. The massive expansion of remote work during the pandemic has dramatically altered where and how employees perform their jobs. Digital technologies played a crucial role in facilitating remote work and keeping up operations in times of limited personal interactions, but also helped to set up online platforms and payment systems.

In this paper, we analyze to what extent the pandemic was a push factor for the digital transition, how firms invested in training and how investment impacted firm-level employment and wage outcomes. Our analysis is based on a combination of unique survey and administrative data from Germany. Roughly two thirds of all establishments have invested in some form in digital technologies during the pandemic. Hardware represents the most common type of digital investment, followed by investments in communication and collaboration software. Investments are particularly prominent in large firms, firms in knowledge-intensive services and firms with a large share of regular employees. Moreover, the possibility to have employees working from home is one important driver for updating the digital infrastructure.

Table 8: Digital Investments and Flows for Employment Subgroups

	(1) Inflows	(2) Outflows	(3) Netflows
		Panel A: Skill Groups	
Low-Skilled	0.001	-0.023**	0.032**
	(0.012)	(0.010)	(0.014)
Medium-Skilled	-0.031*	-0.070****	0.043*
	(0.017)	(0.015)	(0.025)
High-Skilled	-0.022**	-0.032***	0.006
	(0.009)	(0.007)	(0.013)
		Panel B: Age Groups	
$\leq$ 30 Years	-0.011	-0.047***	0.045**
	(0.015)	(0.013)	(0.021)
31 to 50 Years	-0.026*	-0.062***	0.039*
	(0.015)	(0.014)	(0.020)
50+ Years	-0.013	-0.025**	0.011
	(0.011)	(0.009)	(0.013)
		Panel C: Gender	
Females	-0.024	-0.049***	0.028
	(0.015)	(0.013)	(0.020)
Males	-0.030*	-0.065***	0.048**
	(0.016)	(0.014)	(0.023)
No. Firms	1854	1854	1854
Observations	63479	63479	63479

Notes: The table shows the estimated β_3 coefficients based on equation (5), where all specifications include firm fixed effects, time (year *times* month) fixed effects and firm-specific time trends. Column (1) studies monthly inflows at the firm level, column (2) monthly outflows and column (3) monthly netflows defined as inflows minus outflows as dependent variables. Each dependent variable is transformed with the inverse hyperbolic sine to account for the large number of zeros in the flows. Panel A splits the flows by skill level, low-skilled individuals are defined as having no vocational or school degree, medium-skilled individuals have completed vocational education and high-skilled have college degrees. Panel B considers different age groups and Panel C reports results for flows by gender. Inflows refer to the month a person starts working for a firm and outflows refer to the last month a person worked at a firm. To calculate netflows, we use inflows in month t and outflows in month $t-1$. Standard errors reported in brackets are clustered at the establishment level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Investments in digital technologies have been accompanied by an increase in additional training needs such as acquiring IT skills or skills in online communication. Investing firms not only recognized the training need, but also provided more training for their workforce. The complementarity between investments and training in digital tools is particularly pronounced among firms that had to invest more in digital technologies because of the pandemic.

We then demonstrate that investments in digital technologies helped establishments to cushion the employment effects of the economic downturn in the pandemic. Investors had to send fewer regular workers into short-time work, had more employees working normal hours and had to lay off fewer marginal workers than non-investing firms. Finally, we show that firms in the service sector and younger, medium-skilled workers as well as men benefited the most from the insurance effect of digital technologies.

All in all, the pandemic not only forced firms to quickly adapt to a health crisis, it also accelerated the diffusion and use of digital technologies. These investments are long-lasting. Therefore, it can be expected that the associated changes in firms' work processes and more flexible work arrangements are here to stay (Barrero et al., 2021).

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Appendix

A Survey Questions

1. *Question on investments in digitalisation during COVID-19*

   Since the beginning of the COVID-19 crisis, has your establishment made investments in the field of IT or digitalisation, whether in terms of hardware, software or staff?

2. *Question on type of investment*

   In which of the following areas has your establishment made investments since the beginning of the COVID-19 crisis?

   (a) Hardware, e.g. computers, laptops, tablet computers, smartphones, webcams or headsets
   (b) Software for collaboration on and administration of shared documents, e.g. SharePoint or Google Doc
   (c) Software for digital communication and process automation, e.g. Microsoft Teams or Zoom
   (d) Remote access to the establishment's internal files, e.g. VPN connection
   (e) Investment in faster internet access
   (f) Data protection or IT security
   (g) Recruitment of IT specialists
   (h) Other area

   Was the investment made as a result of the COVID-19 crisis or was it irrespective of the crisis?

3. *Question on diffusion of digital technologies*

   In general, has the COVID-19 crisis sped up or slowed down the introduction or expansion of new digital technologies in your establishment or has there been no change?

4. *Question on training needs*

   The COVID-19 crisis may have highlighted further training needs among the employees in some areas. Do you see a need for further training – at least for some of your employees – in the following competences and skills? Or are these competences and skills not relevant in your establishment?

   (a) Skills in IT applications, e.g. Microsoft Office
   (b) Specialist IT knowledge and software programming
   (c) Communication and cooperation skills, also using digital communication media, such as Microsoft Teams, Skype or Zoom
   (d) Management skills, such as management from a distance
   (e) Autonomy, planning and organisation skills, in the office or when working from home
   (f) Data protection in the office or when working from home

5. *Questions on training offered*

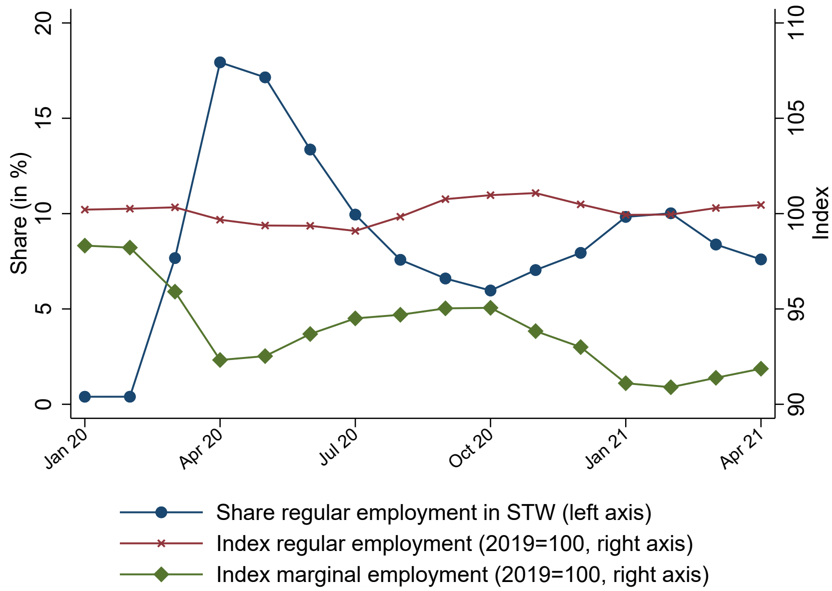
(a) Has your establishment conducted training courses on IT topics since the beginning of the COVID-19 crisis?

(b) Has the volume of IT training been increased or decreased as a result of the COVID-19 crisis or has it remained roughly unchanged?

(c) Do you think your establishment will conduct training courses on IT topics in 2021 and 2022?

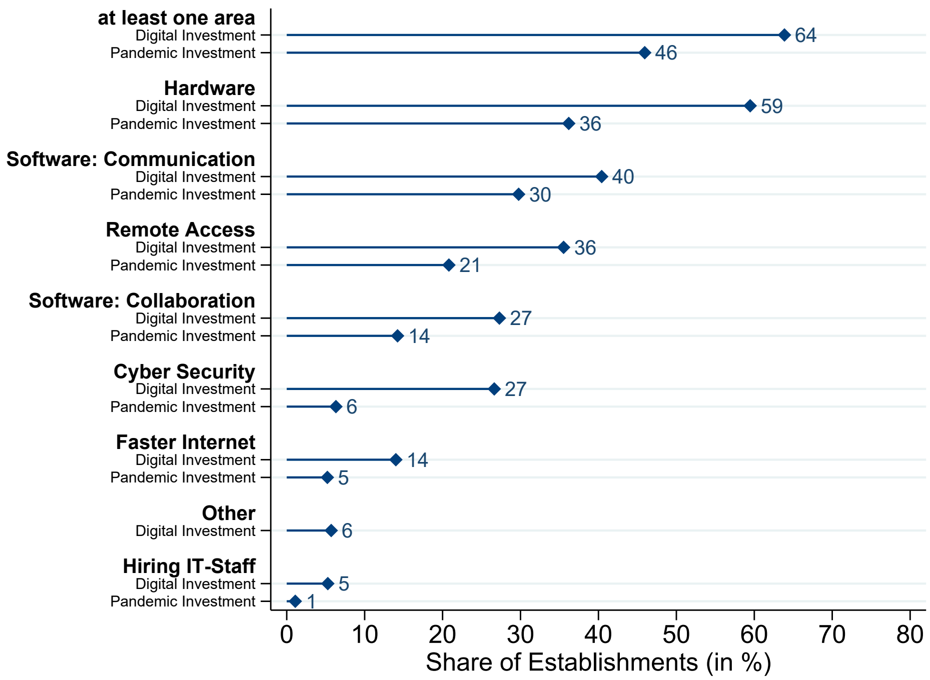
B Additional Results

Figure A.1: Evolution of Employment in Germany during the Pandemic



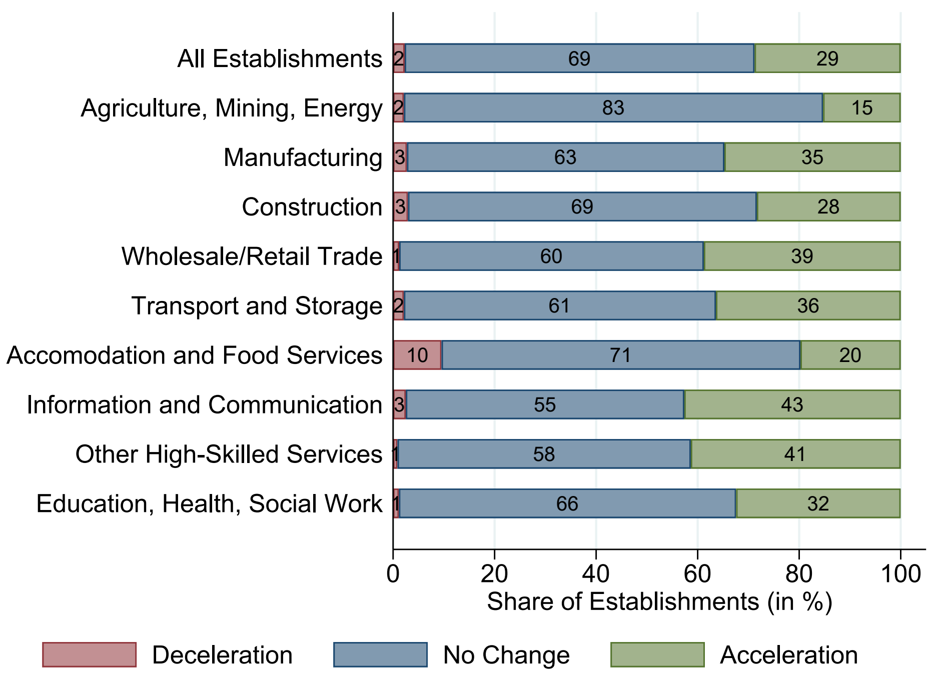
Notes: The figure shows how different types of employment developed in Germany between January 2020 and April 2021. The share of regular employment in short-time work (STW) is the number of persons in STW divided by the total number of persons that are in contributory employment. Regular and marginal employment are indexed to the average values of 2019. Data on the employment type totals stem from the Federal Employment Agency.

Figure A.2: (Pandemic) Investments in Digital Technologies



Notes: The figure shows the percentage of establishments undertaking investments in one of the specified digital technologies and the percentage of establishments undertaking investments due to the pandemic. For the category 'Other', no reason for the investment was elicited in the survey. $N = 1,814$ establishments.

Figure A.3: Diffusion of Digital Technologies by Detailed Sectors



Notes: The figure reports whether the pandemic has accelerated, decelerated or not affected the adoption or diffusion of digital technologies in the establishment. $N = 1,814$ establishments.

Table A1: Summary statistics

	Investment			Pandemic Investment		
	Yes	No	Difference	Yes	No	Difference
	(1)	(2)	(3)	(4)	(5)	(6)
Establishment characteristics						
Employees	106.76	33.56	73.20***	123.35	64.13	59.22***
	(201.16)	(73.88)	(6.55)	(196.18)	(207.72)	(13.33)
Log median daily wage	4.23	3.92	0.30***	4.30	4.05	0.24***
	(0.66)	(0.71)	(0.03)	(0.63)	(0.70)	(0.04)
Firm Wage Premia	0.26	0.18	0.08***	0.28	0.21	0.07***
	(0.21)	(0.25)	(0.01)	(0.19)	(0.24)	(0.02)
Non-knowledge-intensive production	0.20	0.28	-0.08***	0.19	0.23	-0.03
	(0.40)	(0.45)	(0.02)	(0.40)	(0.42)	(0.03)
Knowledge-intensive production	0.06	0.03	0.03***	0.07	0.03	0.04***
	(0.23)	(0.16)	(0.01)	(0.26)	(0.16)	(0.01)
Non-knowledge-intensive services	0.53	0.53	0.00	0.51	0.58	-0.07**
	(0.50)	(0.50)	(0.02)	(0.50)	(0.49)	(0.03)
Knowledge-intensive services	0.18	0.14	0.04**	0.20	0.15	0.05**
	(0.39)	(0.35)	(0.02)	(0.40)	(0.36)	(0.02)
Information and communication	0.02	0.02	0.00	0.03	0.01	0.01
	(0.15)	(0.14)	(0.01)	(0.16)	(0.11)	(0.01)
Workforce composition						
Young workers	0.24	0.24	0.00	0.24	0.25	-0.00
	(0.17)	(0.22)	(0.01)	(0.17)	(0.19)	(0.01)
Prime-aged workers	0.43	0.41	0.01	0.43	0.41	0.02*
	(0.16)	(0.23)	(0.01)	(0.15)	(0.18)	(0.01)
Older workers	0.33	0.34	-0.01	0.33	0.34	-0.02
	(0.18)	(0.26)	(0.01)	(0.17)	(0.20)	(0.01)
Female workers	0.47	0.49	-0.01	0.47	0.50	-0.03
	(0.29)	(0.34)	(0.02)	(0.28)	(0.31)	(0.02)
Foreign workers	0.10	0.12	-0.02*	0.10	0.11	-0.02
	(0.16)	(0.20)	(0.01)	(0.14)	(0.19)	(0.01)

	Investment			Pandemic Investment		
	Yes	No	Difference	Yes	No	Difference
	(1)	(2)	(3)	(4)	(5)	(6)
Low-skilled workers	0.14	0.15	-0.01*	0.13	0.15	-0.01
	(0.13)	(0.18)	(0.01)	(0.13)	(0.15)	(0.01)
Medium-skilled workers	0.67	0.71	-0.04***	0.66	0.69	-0.04***
	(0.23)	(0.26)	(0.01)	(0.23)	(0.23)	(0.01)
High-skilled workers	0.18	0.13	0.06***	0.20	0.15	0.05***
	(0.21)	(0.22)	(0.01)	(0.22)	(0.20)	(0.01)
Full-time workers	0.62	0.55	0.07***	0.65	0.57	0.08***
	(0.30)	(0.33)	(0.02)	(0.30)	(0.31)	(0.02)
Regular workers	0.79	0.73	0.06***	0.81	0.75	0.06***
	(0.21)	(0.25)	(0.01)	(0.20)	(0.21)	(0.01)
Unskilled/semi-skilled occupations	0.20	0.23	-0.04***	0.19	0.23	-0.04***
	(0.22)	(0.28)	(0.01)	(0.21)	(0.24)	(0.01)
Specialist Occupations	0.55	0.60	-0.05***	0.54	0.59	-0.05***
	(0.27)	(0.31)	(0.01)	(0.27)	(0.27)	(0.02)
Complex specialist occupations	0.13	0.10	0.03***	0.14	0.11	0.04***
	(0.18)	(0.19)	(0.01)	(0.18)	(0.17)	(0.01)
Highly complex occupations	0.12	0.07	0.05***	0.13	0.08	0.05***
	(0.18)	(0.16)	(0.01)	(0.19)	(0.16)	(0.01)
Working with screens	0.58	0.50	0.08***	0.61	0.51	0.10***
	(0.33)	(0.37)	(0.02)	(0.32)	(0.33)	(0.02)
Observations	1,167	659		840	327	

Notes: Firm wage premia are measured as firm fixed effects (from an AKM wage regression with firm and worker fixed effects) in 2010-2017. Workforce characteristics are reported in June 2019. Young workers are below 30 years of age, prime-aged workers are between 30 and 50 years of age and older workers are older than 50 years of age. Low-skilled workers are those without a vocational degree, medium-skilled workers have a vocational degree and high-skilled workers have a college or university degree. Regular employees are all workers subject to social security contributions, thus excluding marginal workers. Columns (1), (2), (4) and (5) show standard deviations in parentheses. Columns (3) and (6) show robust standard errors in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table A2: Which Digital Technologies Did Establishments Invest In?

	(1) Hardware	(2) Software: Collaboration	(3) Software: Communication	(4) Remote Access	(5) Faster Internet	(6) Cyber Security	(7) IT staff	(8) Other
Firm Wage Premium	0.055	0.033	0.041	0.044	-0.012	-0.088	0.023	0.051*
	(0.057)	(0.061)	(0.065)	(0.064)	(0.054)	(0.060)	(0.036)	(0.029)
Share Regular Workers	0.223***	0.054	0.239***	0.147	0.017	0.158*	0.123*	-0.024
	(0.084)	(0.086)	(0.088)	(0.094)	(0.068)	(0.089)	(0.065)	(0.041)
Share Screen Work	0.100**	0.162***	0.136***	0.115**	0.102***	0.071	0.010	0.025
	(0.049)	(0.053)	(0.053)	(0.054)	(0.038)	(0.052)	(0.031)	(0.028)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1527	1527	1527	1527	1527	1527	1527	1527
MeanY	0.63	0.29	0.43	0.38	0.15	0.28	0.06	0.06

Notes: The table reports marginal effects from logit regressions based on equation (2), where the dependent variables are indicators equal to one if an establishment invested in the type of digital technology indicated in the top row; and zero otherwise. The firm wage premia (AKM fixed effects) are estimated for the period 2010 to 2017 (Bellmann et al., 2020b). AKM fixed effects are not available for newly established firms. Control variables are sector, firm size, a dummy for East Germany and degree of urbanization. Included workforce characteristics are shares of: occupational requirement levels (4 categories), age groups (3 categories), German nationality, women, full time workers, skill levels (3 categories). All workforce and establishment characteristics are measured in the pre-pandemic period (June 2019). Standard errors in brackets are clustered at the establishment level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$