The Pandemic Push: Digital Technologies and Workforce Adjustments*

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Abstract

Using a combination of 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 (three quarters of which because of the pandemic), in particular in hardware and software to enable decentralized communication, management and coordination. The investments further encouraged additional firm-sponsored training despite the pandemic-related restrictions. We then demonstrate that the additional investments helped firms to insure workers against the negative economic consequences of the pandemic. Firms that made additional investments had to rely less on short-time work, were more likely to keep their regular employees at work and had to lay off fewer marginal workers.

Keywords: Innovation, digital technologies, COVID-19 pandemic, investment, training, employment, worker flows

JEL: D22, E22, J23, J63

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1 Introduction

The COVID-19 pandemic has moved much of the world online with internet traffic expanding by up to 60% in some countries (Baruffaldi et al., 2020). Families rearranged their division of labor, employees shifted to work from home, consumers went online and firms adopted new digital business models and processes. While the digital transition of the economy and society has been underway for some time, the last years saw a sizable acceleration. Many of these transformations are here to stay and are likely to leave a deep imprint on the labor market and the economy.

In this paper, we analyze whether the pandemic was a push factor for the digital transition. We ask which firms have actually invested during, but also because, of the pandemic; and what type of digital tools they invested in. Investments alone are unlikely to be sufficient to make productive and efficient use of digital technologies. The workforce also needs to know how to use and work with the new technical capabilities. In a second step, we therefore turn to the question whether firms increase their demand for training; and whether firms actually offered more employer-sponsored training during the period – despite pandemic disruptions and the associated economic downturn. In a third step, we investigate whether digital investments impacted firm's employment and wage responses to the health crisis; and who bears the adjustment costs.

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 increases (see, e.g., Bloom et al., 2007). The severe recession in 2020 that disrupted supply chains and customer relations dramatically increased economic uncertainty for many firms (Altig et al., 2020). At the same time, investments in digital tools that facilitate remote work and exchange enable firms to substitute for many personal interactions in their day-to-day operations. The widespread use of telework is one indication that firms adjusted their workflows and that these adjustments remained in place even when the pandemic subsided (Bloom et al., 2020). Digital technologies provide many tools to assist teleworkers and managers: collaboration software to hold meetings, cloud computing to share files, online management tools to coordinate activities and tasks. These tools build on infrastructure including hardware, secure access and data protection that firms might need to invest in or expand.

Digital technologies might thus help firms to cushion the blow to labor demand and supply disruptions during the pandemic but also have longer-lasting effects on workforce composition and wages. Moreover, 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 would even increase. In that case, the distributional effects of the digital transition would be even more skewed towards the technological leaders, which might further increase firm heterogeneity in pay and working conditions in the long-run.

Labor market policies also have an influence on the adjustment behavior of firms during the pandemic. Many European countries relied on generous provisions for short-time work to avoid job displacements and help firms adjust to the economic disruptions of the pandemic (OECD, 2021; Giupponi et al., 2022).[1] The instrument had already been used extensively during the financial crisis of 2008 to keep layoffs and unemployment low. Unlike the U.S., which saw a dramatic spike in unemployment during the financial crisis and again during the pandemic, unemployment increased much less in countries with short-time work (OECD, 2021).[2]

Our analysis studies firms in Germany during the pandemic. Germany provides an interesting case study because it has lagged behind the broad diffusion of digital technologies. For our analysis, we link a unique establishment survey that was conducted during the pandemic with administrative matched employer-employee data.[3] The representative survey was set up to obtain information about the economic situation of establishments and strategies that they adopted during the pandemic. The survey questions in this paper were designed by the authors and were fielded to around 2,000 establishments in February of 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 their workforce and wages, industry and location.

We have four main findings. First, we find that two out of three firms invested in digital technologies in the first year of the pandemic, a majority of which (75%) invested because of the pandemic. On

[1]Short-time work stabilized employment levels of regular workers who are eligible for short-time work compared to marginal employees who are not (see Appendix-Figure A.1).

[2]Evidence from the Great Recession indicates that short-time work indeed reduced layoffs, but may have delayed adjustments to changing economic conditions (Boeri and Bruecker, 2011; Giupponi and Landais, forthcoming).

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

average, firms invested in three digital tools, especially in hardware, communication software and data access. Investing firms are typically larger, pay higher wages, have a more skilled workforce and produce in knowledge-intensive sectors than firms that did not invest. Zooming in on firms that invested because of the pandemic further reveals that firms in knowledge-intensive production are more likely, while firms in East Germany much less likely to invest in digital technologies. Therefore, the pandemic was indeed a push factor for the digital transition in as far as a high share of firms undertook investments in digital technologies; at the same time, it also increased the digital divide between firms as it was mostly larger firms in West Germany producing in knowledge-intensive industries and services that invested.

Second, we demonstrate that training the workforce to use the digital tools is an important complement to investments in hardware, software and infrastructure. 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 were forced or induced by the pandemic to invest in digital technologies report having substantially more training needs than firms that invested in digital tools independently of the pandemic. Most firms, in particular those that invested because of the pandemic, 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 find that investing firms were able to better insure their employees against the economic shock of the pandemic. For both investing and non-investing firms, the pandemic led initially to a sharp reduction in total employment followed by a recovery at 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 be laid off in economic downturns. Investing firms were more likely to keep their marginal workers than non-investing firms. As we see less negative effects for both regular employees and marginal workers, these results cannot be explained by investing firms substituting marginal workers for regular employees. Overall, the employment results indicate that investors were better able to keep up their normal operations and insure their whole workforce against job disruptions than non-investors. We conduct a number of robustness checks to provide further support to the finding that investments led to a more favourable development of employment outcomes (rather than merely reflecting firm heterogeneity).

Fourth, we find few effects on firm wages overall or conditional on workforce composition. We do find some indication that firms postponed salary increases, however. Yet, the postponement effect is similar in investing and non-investing firms. Like other studies on the German labor market, we find that employment rather than wages are the dominant adjustment mechanism to labor market shocks in Germany (see, e.g., Dustmann et al., 2016; Gathmann et al., 2020).

Furthermore, we perform a range of additional tests to ensure that firms that invested in digital tools during the pandemic did not have more favorable employment or wage trajectories than non-investing firms even before the pandemic, have deeper pockets or are less severely affected by the pandemic. Our battery of robustness checks corroborates the 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: the rapidly growing literature on the pandemic; studies on firm-level adoption of new technologies; and studies on the labor market consequences of new technologies. A large literature has examined the consequences of the pandemic for labor demand, employment and wages and the impact of alternative government policies to confine it (see, e.g., Adams-Prassl et al., 2020; Forsythe et al., 2020). A related literature has shown the widespread use of teleworking and its impact on work organization and firm outcomes (Bloom et al., 2020; Barrero et al., 2021; Kagerl and Starzetz, 2022). On the regional level, studies have shown that areas with higher levels of pre-pandemic IT capital were economically more resilient in the pandemic, both in the US (Oikonomou et al., 2023) and in Germany (Ben Yahmed et al., 2022).

Moreover, we contribute to the literature on firms' decision to adopt new technologies (Acemoglu et al., 2022; Zolas et al., 2020). Existing evidence indicates that adopters of robots or automation technology are typically larger and more productive with a more skilled workforce than non-adopters (see Acemoglu and Restrepo (2022) for the US; Aghion et al. (2020) for France; Koch et al. (2021) for Spain). We find a similar result for firms adopting digital technologies, which are mostly used in white-collar jobs rather than for automating production processes. Investments in robots only make up a tiny share of overall investment in equipment (just 0.3%) and robots are heavily concentrated in a few industries. Our analyses covers a different type of digital technologies that complements workers, especially during the pandemic, and have been used in a broad range of industries and economic sectors. Moreover, we study the investment decision in a severe health and economic crisis (see also Babina et al., 2020, for evidence from the Great Depression). Many firms became more cautious with large-scale investment projects though there were marked differences across sectors and firms. Other firms had to reconsider investment plans as the pandemic required adjustments in the organization of work and interactions (Barth et al., 2022).

Finally, our analysis also contributes to studies on the labor market impacts of innovations like automation, robots and AI-related technologies (Babina et al., forthcoming). The above mentioned firm-level studies of adoption mostly find that employment grows faster in firms adopting robots than in non-adopting firms. Studies on the labor market effects of robots (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020; Dauth et al., 2021; Koch et al., 2021; Humlum, 2019; Benmelech and Zator, 2022) typically find little displacement effects from robots at the firm, industry or local labor market level. In many firms, these investments are used to address labor shortages and compensate for unfilled vacancies. Other studies point to a composition effect: while adopting firms grow, non-adopting firms shrink (Koch et al., 2021); and while jobs in manufacturing seem to decrease with robots, additional jobs are created in the service sector (Dauth et al., 2021; Gregory et al., 2022). The only exception to this pattern are Acemoglu and Restrepo (2020) for the U.S. and Bonfiglioli et al. (2020) for France; they find stronger displacement effects if one properly accounts for demand-side changes or firm-level differences between adopters and non-adopters.

Closest to our study are two papers on automation and digital technologies. The first one studies investments in cloud computing, online platforms, but also smart factories and robots in German plants (Genz et al., 2021); the second one uses a Norwegian firm survey to analyze how the pandemic affected investments in digital technologies during the pandemic (Barth et al., 2022). Similar to our paper, Barth et al. (2022) find that the pandemic had a considerable impact on firms' investment behavior and that it contributed to a widening of the digital divide. Moreover, using survey responses they find that investments also affect how firms assess their *expected* labor requirements. In contrast to their study, our empirical analysis of employment outcomes is based on *actual* rather than expected outcomes. Moreover, we are able to link our survey data to administrative data which allows us to account for potential differences in pre-pandemic development of employment outcomes of investing and non-investing firms. Our study focuses less on automation technologies but rather on digital tools for white-collar jobs. We also do not find evidence that digital technologies replace workers in adopting firms though we do see shifts in the composition of the workforce. We further investigate how investments complement training needs and activities, which has not been studied in the earlier literature. Finally, we analyze a period of severe recession and high economic uncertainty during the pandemic that hit Germany in 2020.

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 reports the results on who invested in digital tools and the types of digital technologies firms invested in. Section 5 shows the results on training, employment and workforce composition, while Section 6 reports several robustness checks and explores the heterogeneity of findings across firms. 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. Establishments were sampled from the universe of privately-owned establishments that are registered at the German Federal Employment Agency.[4] Each wave is representative of the private sector in Germany. Further information on the survey can be found in Bellmann et al. (2022) and Backhaus et al. (2022),

The information on investments in digital technologies and firm-provided training come from the ninth wave, which collected data from 1,941 establishments in February 2021. 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.[5] We also know whether the firms invested because of the pandemic or would have invested in any case. In addition, we asked about firms' training needs in areas such as leadership or IT skills; and whether firms have expanded or reduced their training activities during the pandemic. We also collected information on the current economic situation of the firm and the impact of the pandemic on its business.

[4]The public sector and extraterritorial organizations are not part of the survey.
[5]See Appendix A for detailed information on the survey questions.

2.2 Linked Survey and Administrative Data

To analyse how investments in digital technologies affected workforce employment and wages, we link the survey to administrative data from social security records.[6] 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.[7] 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 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 the pandemic, while marginal employees were not. We also observe the number of workers leaving an establishment and the number of new employees at 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 of 2020, up to six million employees were in short-time work with a reduction of working hours of 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).[8]

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. Censoring does barely affect median wages at the

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

[7]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).

[8]The proxy is constructed from information about whether working with screens belongs to the task contents of the respective occupation.

firm level, compared to mean wages. Furthermore, the data provides information about establishment quality as given by the estimated establishment fixed effects from an AKM-style wage decomposition. Based on pre-pandemic data (2010-2017), is a measure of the average firm wage premium (see Bellmann et al., 2020b; Abowd et al., 1999, 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 and opportunity to use digital technologies.

3 Estimation Approach

3.1 Investment Decisions

We start out with investigating 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 pandemic; and zero otherwise. The matrix $\mathbf{X}$ 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 for the median wage in the establishment to account for differences in production technology and productivity. 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:

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

where $DigInvest_f^d$ is an indicator that takes the value one if establishment f has invested in 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-level control variables as described above.

3.2 Training Needs and Training Activities

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

$$Y_f = \beta_3 DigInvest_f + \boldsymbol{\gamma_3}'\mathbf{X}_f + \varepsilon_{3f}, \tag{3}$$

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 like 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 in 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. We then estimate variants of the following model:

$$Y_{ft} = \beta_4(DigInvest_f \times Post_t) + \theta_f + \psi_t + (\theta_f \times t) + \varepsilon_{4ft} \tag{4}$$

where Y_{ft} now denotes firm-level outcomes like employment, the share of workers in short-time work, or median wages in month t. $DigInvest_f$ is an indicator equal to one if an establishment invested in digital technologies; and zero otherwise. $Post_t$ is an indicator equal to one in 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. 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 some specifications, we also include establishment-specific time trends $\theta_f \times t$ to capture differential employment trajectories or differential demand-side trends that are unobserved but evolve linearly over time.

To analyze the dynamics of employment adjustments graphically, we extend the specification in (4) to an event-study-type framework. Specifically, we replace the time indicator $Post_t$ with monthly dummies and estimate the following model:

$$Y_{ft} = \sum_{m \neq Feb20} \beta_{5m}(DigInvest_f \times \mathbb{1}(t = m)) + \theta_f + \psi_t + \varepsilon_{5ft} \tag{5}$$

where t again refers to a month in the period from January 2018 to December 2020.

Our main parameters of interest are β_4 and β_5, 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 to investing firms in the absence of investments.

A key concern of our estimation strategy is that firms that invested in digital technologies are a selected sample of firms possibly with deeper pockets, higher productivity or better employment and wage trajectories even before the pandemic than firms that did not invest. We use a number of different strategies to address these concerns. All our specifications control for firm fixed effects to adjust for unobserved heterogeneity as well as detailed year-by-month dummies to capture the dynamics of the pandemic situation. Most specifications also include firm-specific linear trends to capture differences in employment trajectories between investing and non-investing firms. Moreover, we use event studies to check for pre-pandemic differences in the development of employment between investing and non-investing firms.

Firm fixed effects and firm-specific trends might not be enough to capture pre-existing differences in investment or employment dynamics. We run a number of additional robustness checks restricting the sample to high-performing firms, firms that report facing no financial constraints and firms reporting less severe demand disruptions to check whether these could explain the observed differences in labor market outcomes between investing and non-investing firms. The different strategies fail to find evidence for these alternative explanations.

A related 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 additional 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 that affect some industries more than others. The results indicate that differences across regions and industries cannot explain the observed differences between investing and non-investing firms. We report these additional robustness checks after our main results.

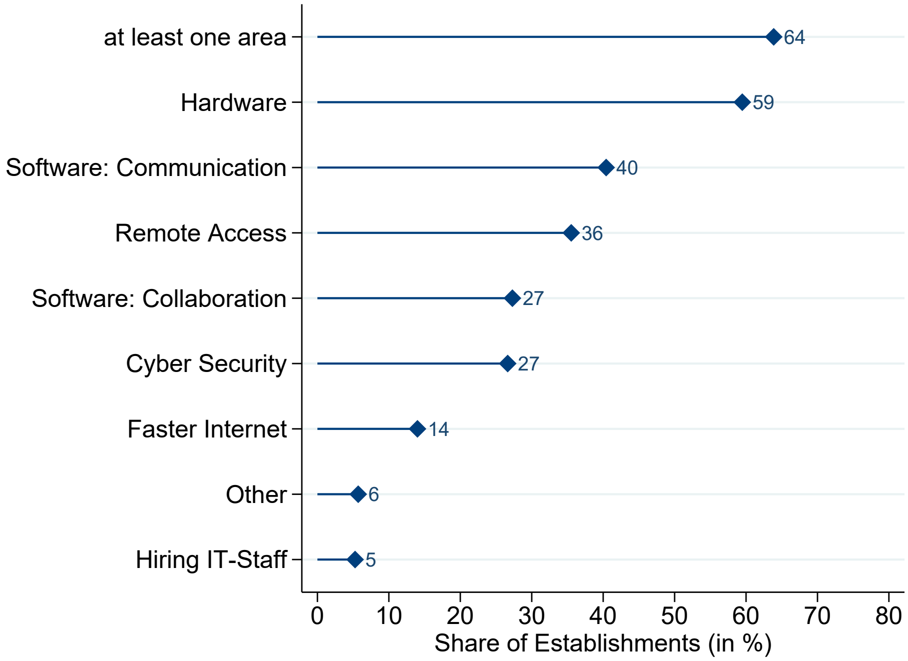
4 Empirical Evidence on Investments in Digital Technologies

4.1 The Pandemic as a Push Factor

We start out with descriptive evidence on the digital investments undertaken and whether they were induced by the pandemic or not. Figure 1 illustrates the type of digital technologies invested in: 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. Many establishments undertook multiple investments; the median establishment invested in three types of technologies.

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 necessarily undertaken in response to the pandemic. Firms reported whether the investment was made because of the pandemic or whether it was planned independently of it. Among the group of

Figure 1: Types of Investments in Digital Technologies



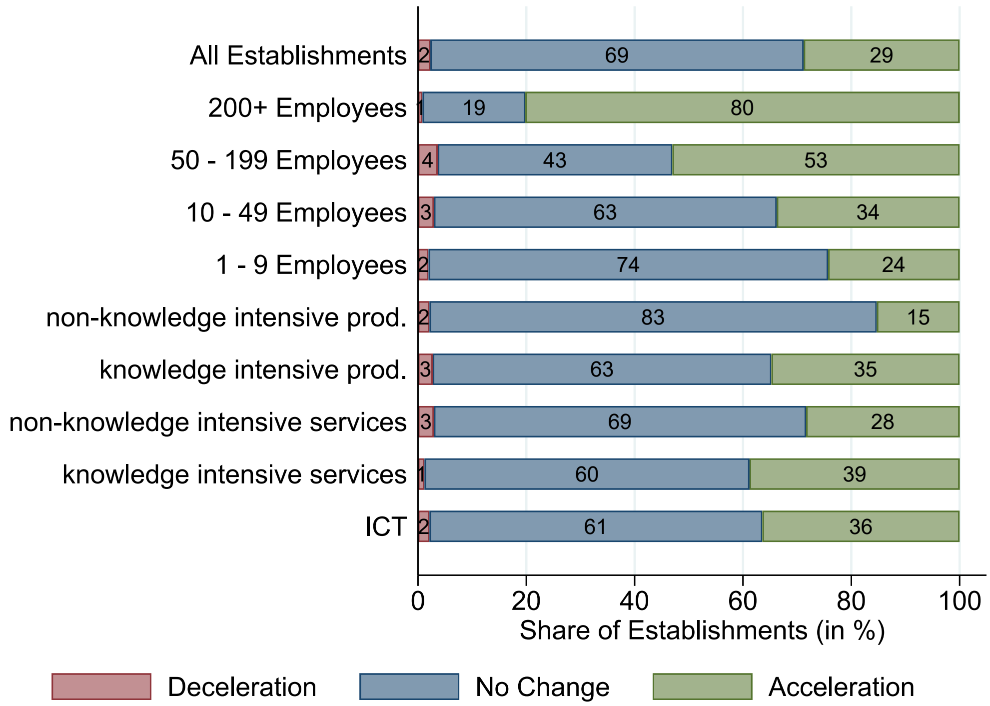
Notes: The figure shows the percentage of establishments undertaking investments in one of the specified digital technologies. $N = 1,814$ establishments.

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, 30% report that the pandemic has accelerated or expanded investments in digital technologies. In contrast, only very few establishments (less than 5%) 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.[9]

[9]Zooming in on industries, Appendix-Figure A.2 reveals 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.

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.

4.2 Who Invests in Digital Technologies?

The evidence thus far 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 and also higher wage premia (as measured by the estimated establishment fixed effects from an AKM wage decomposition) than non-investing firms. Partly, 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 (+6 percentage points) than non-investors, while the age and gender composition is similar. Investors also have a higher share of employees with regular contracts (+6 percentage points) and working full-time (+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 might be 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 whether an establishment invested in at least one digital technology or not. Table 1 reports marginal effects based on the model in equation (1) from Section 3. The key independent variables are firm wage premia, the share of regular workers (i.e. employees subject to social security contributions) and the share of workers whose jobs allow remote work.

Conditional on firm size, sector and workforce composition, firms with higher wage premia are also more likely to invest, albeit not significantly so. The estimate on the AKM-FE in column (1) suggests that a one standard deviation increase in the wage premium ($SD = 0.23$) increases the propensity to invest by roughly 2 percentage points. Moreover, there is a slight positive connection between the share of regular workers and investments. 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 (average is roughly 50%) by 10 percentage points is associated with a higher propensity to invest by 1.1 percentage points. Hence, investments in digital technologies are complementary to the observed shift to telework observed in many countries during the pandemic (Barrero et al., 2021; Kagerl and Starzetz, 2022).

The remaining columns split the investor sample by whether investments were made in direct response to the pandemic – columns (3) and (4) or independently of it – columns (5) and (6). That is, we separately compare the non-investors to pandemic investors and to independent investors. In terms of the firm wage premia, we continue to find positive, but insignificant, relationships with investment, irrespective of the investment reason. For the regular workers, the positive association is mostly driven by the sample of pandemic investors, reflecting a higher willingness to invest on the part of firms if their workers are bound more tightly to the establishment. Similarly, the investment decision's connection to screen workers stems almost exclusively from pandemic investors, consistent with the social-distancing response to the pandemic that required working from home where possible.

Firms might also differ in the types of digital technologies they invested in. It could well be that

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. 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: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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 extent of working with a computer screen, which proxies for the potential of working remotely and using digital technologies, shows a strong positive correlation with investments in software tools and remote access as well as internet capabilities. At the same time, firms that pay higher wages are slightly more likely to invest in hardware and remote access than other firms. We generally find that larger firms and firms in knowledge-intensive sectors are more likely to invest in all types of digital tools.

Overall, investors are positively selected in terms of size, wages and pre-pandemic productivity. Such firms are more likely to have the necessary funds to finance additional investment needs emerging in the pandemic than other firms. Moreover, investments are much more likely to be undertaken by firms with a high-skilled workforce operating in the knowledge-intensive sector, for whom it was feasible to perform their work remotely 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.

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 be 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. 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)).[10]

Panel A of Table 2 shows the average marginal effect 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 strong 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).

In Panel B of Table 2, we compare the corresponding average marginal effects for firms that invested because of the pandemic and those that would have made the investments independently. Firms investing in response to the pandemic have a much higher training need for all skills than establishments that had plans to invest irrespective of the pandemic. The higher need for pandemic-related investments is especially striking for management skills as well as communication and cooperation skills: firms that

[10] As establishments could answer that a particular skill set is not relevant in their business, the table presents average marginal effects from a multinomial logit model 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.

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)
Invested independently	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 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: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

invested because of the pandemic are about 28 percentage points more likely to report 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, establishments with pandemic-related investments saw a nearly 20 percentage points higher need for training in management skills (like how to work with a team online) compared to an increase of only 6 percentage points in firms that invested independently of the pandemic.

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 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.

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

About 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, investing establishments are about 30 percentage points more likely to have carried out training courses than non-investing firms.

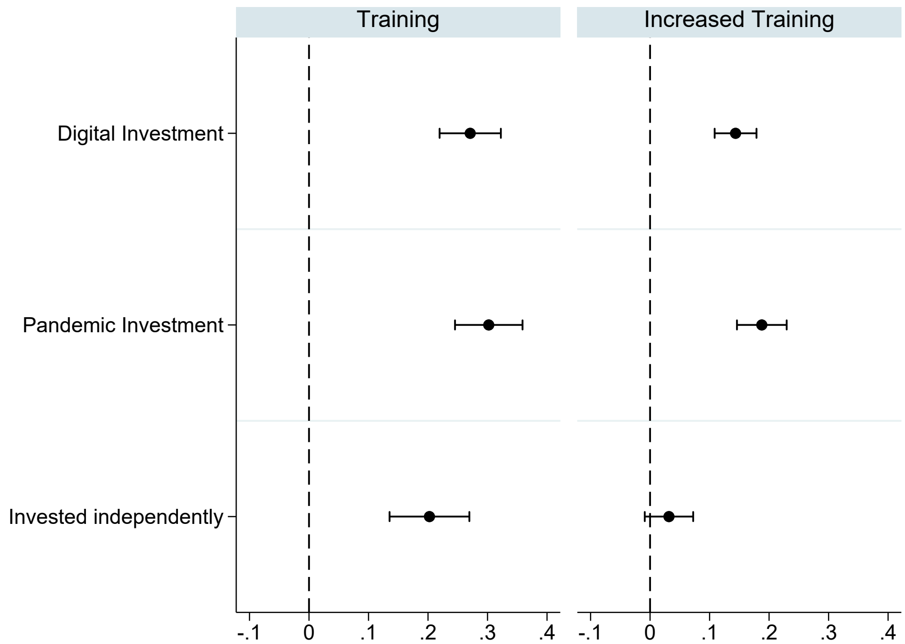
Moreover, firms that invested are also more likely to increase their training efforts during the pandemic. The right panel of Figure 3 shows whether firm-provided training *increased* during the pandemic relative to the pre-pandemic period. Investing firms are 15 percentage points more likely to have 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 train more increased by almost 20 percentage points compared to non-investing establishments. Establishments that invested independently of the pandemic only report a 3 percentage point higher training activity (not significant) than non-investing firms.

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 act 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 (4) from Section 3 to provide systematic evidence on the link between investments and employment adjustments. For a graphical representation and for assessing pre-trends

Figure 3: Investment and Actual Training Activities



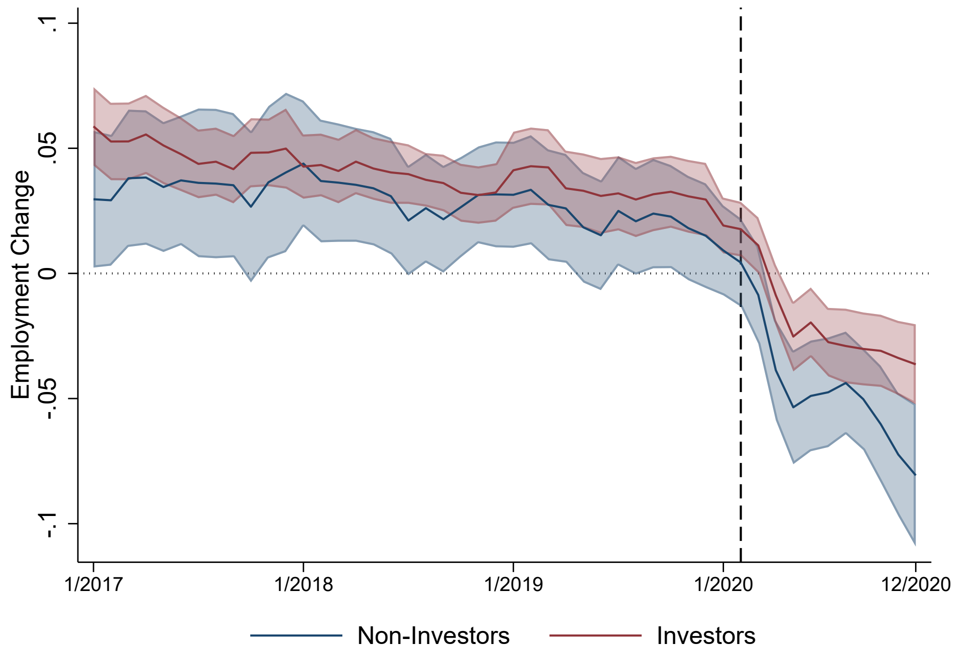
Notes: The figure shows average marginal effects and 95% confidence intervals obtained from regressions of equation (3). 'Digital Investment' is a dummy variable equal to one if the firm has invested in digital technologies in the pandemic. The investors are further split into the two groups 'Pandemic Investment' and 'Invested independently', 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 whether any IT-based training took place during the pandemic's first year. The right panel shows average marginal effects from multinomial logit regressions 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.

in employment, we also use an event study framework (according to equation (5) from Section 3).

5.1 Investments and Total Employment

Figure 4 shows unconditional changes in (log) total employment at monthly frequency. The graph reveals that investing and non-investing firms both experienced employment growth between 2% and 5% per year in the pre-pandemic period. When the pandemic hit in March 2020, as indicated by the vertical dashed line, employment plunged drastically in all firms. 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

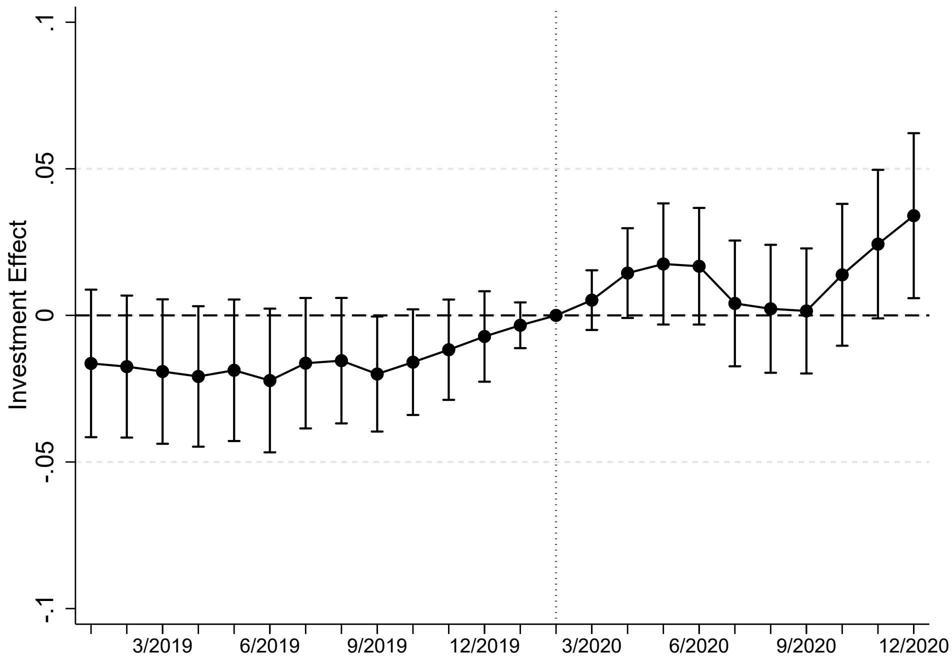


Notes: The graph shows the mean yearly change for total (log) employment separately for investors and non-investors and their respective confidence intervals (± 2 SEs of the mean). The balanced sample consists of $1,711$ firms that are observed in the administrative data over the whole period.

We next provide event study estimates for employment in investing and non-investing firms using specification (5). The estimates are shown in Figure 5; the figure shows that there is no differential pre-trend in employment between investing and non-investing firms. If anything, employment growth in investing firms was slightly lower than in non-investing firms before the pandemic, though none of the pre-pandemic effects are statistically significant at conventional levels. After the onset of the pandemic, investing firms see fewer 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 coefficients and 95%-CIs from model (5) with total log (monthly) employment as the dependent variable, i.e. time and firm fixed effects are included and standard errors are clustered at the establishment level. The reference month is February 2020.

Table 3 shows the coefficient estimates of β from (4) for all firms as well as separately for firms that invested because of the pandemic and firms that invested independently of it. Column (1) summarizes Figure 5 – comparing the average of the estimates until February 2020 with the average of the estimates from March 2020 onward. The coefficient in column (1) suggests that the change in employment from the pre-pandemic to the post-pandemic period was, on average, 3.4 percentage points higher among investors than non-investors. When we differentiate by the reason for investment (column (2)), we find a similarly sized positive effect for pandemic-induced and independent investment, but only the former is statistically significant.

We next include establishment-specific trends to control for any differences in employment trajectories between investing and non-investing firms – though the visual evidence in Figure 5 does not indicate differential pre-trends. The results are shown in column (3) and column (4). Once trends are included, the difference in the post-treatment change in employment between investors and non-investors becomes small and statistically insignificant (column (3)). This very small positive association seems to be driven by pandemic investors (column (4)). In sum, there seems to be some differences in

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)
Invested independently		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 estimates based on specification (4). The dependent variable is log total (monthly) employment in an establishment. 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 reference category 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: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

how investing firms adjust their workforce during the pandemic than non-investing firms though the results for total employment are inconclusive.

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 so-called *Minijobs*, are not. Hiring and firing marginal employees is considerably easier compared to regular employees because they are not covered by strict employment protection rules.

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 working hours of their regular employees in a month with the earnings difference 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.[11] About six million employees, or one out of five regular employees, were in short-time work in May 2020 and around one million workers continued to be covered by short-time work by August 2021. Workers in short-time work are still counted as part of regular employment even if they work fewer or even zero hours. As such, employment records of the establishment do not capture

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

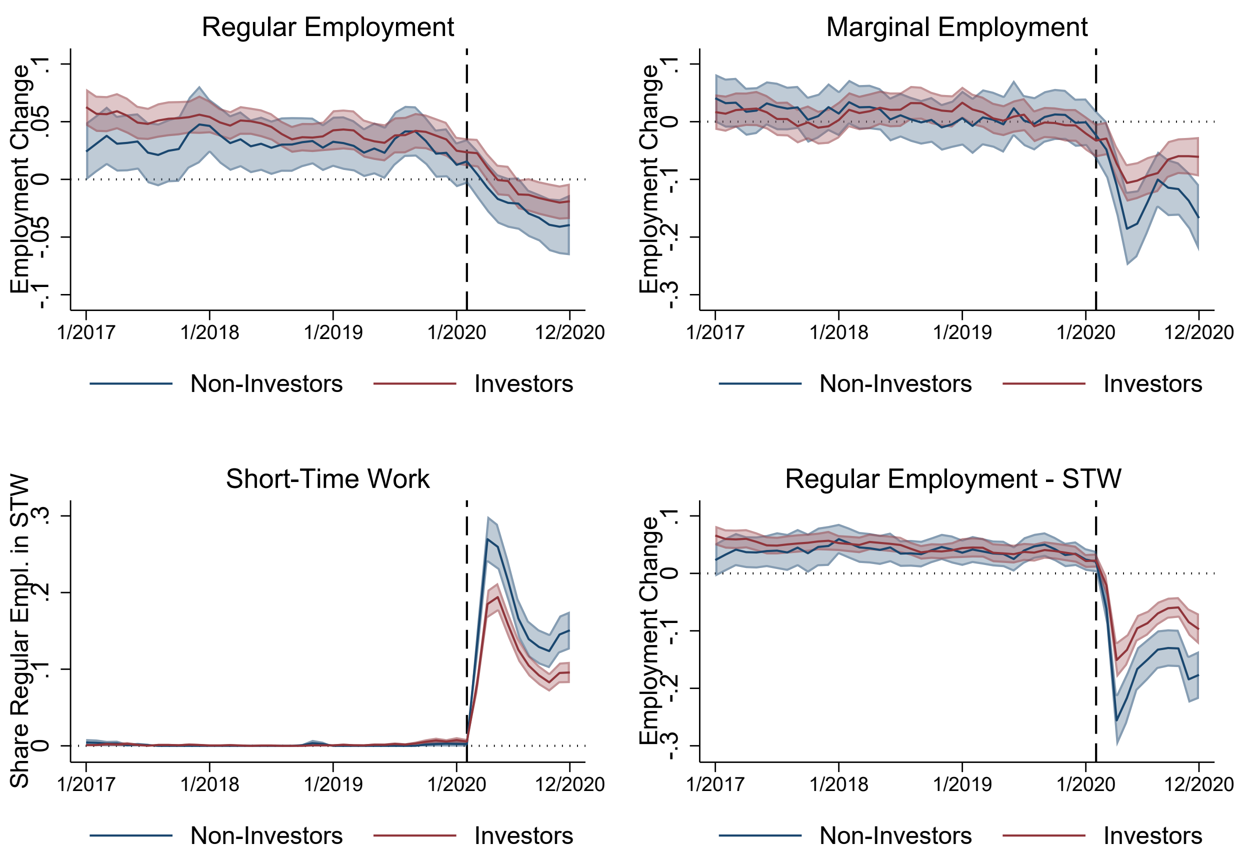
this margin of adjustment. We therefore use administrative records on the number of employees in short-time work for each establishment and month.[12]

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. Alternatively, employers could reduce the labor input among their regular workforce either through short-time work or layoffs. 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. 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 of regular employees depends on the relative importance of each group in the production and the associated labor costs during the pandemic.

Figure 6 shows changes among different types of employment in 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 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 in response to the pandemic than investing firms. The bottom left panel shows the evolution of short-time work, which was mostly zero before the pandemic. When the pandemic hits, 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 early fall 2020 before picking up again at the end of year. This pattern closely tracks the severity of the pandemic in Germany in terms of social distancing and lockdown measures. Finally, the bottom right panel tracks the number of regular employees that keep their job without being put on short-time work schemes. The pre-pandemic evolution is very similar, largely because short-time was not used by firms then. From March 2020 onward, firms start making use of short-term work and the number of regular employees not in short-time work drops rapidly. This

[12]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 out reimbursements.

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

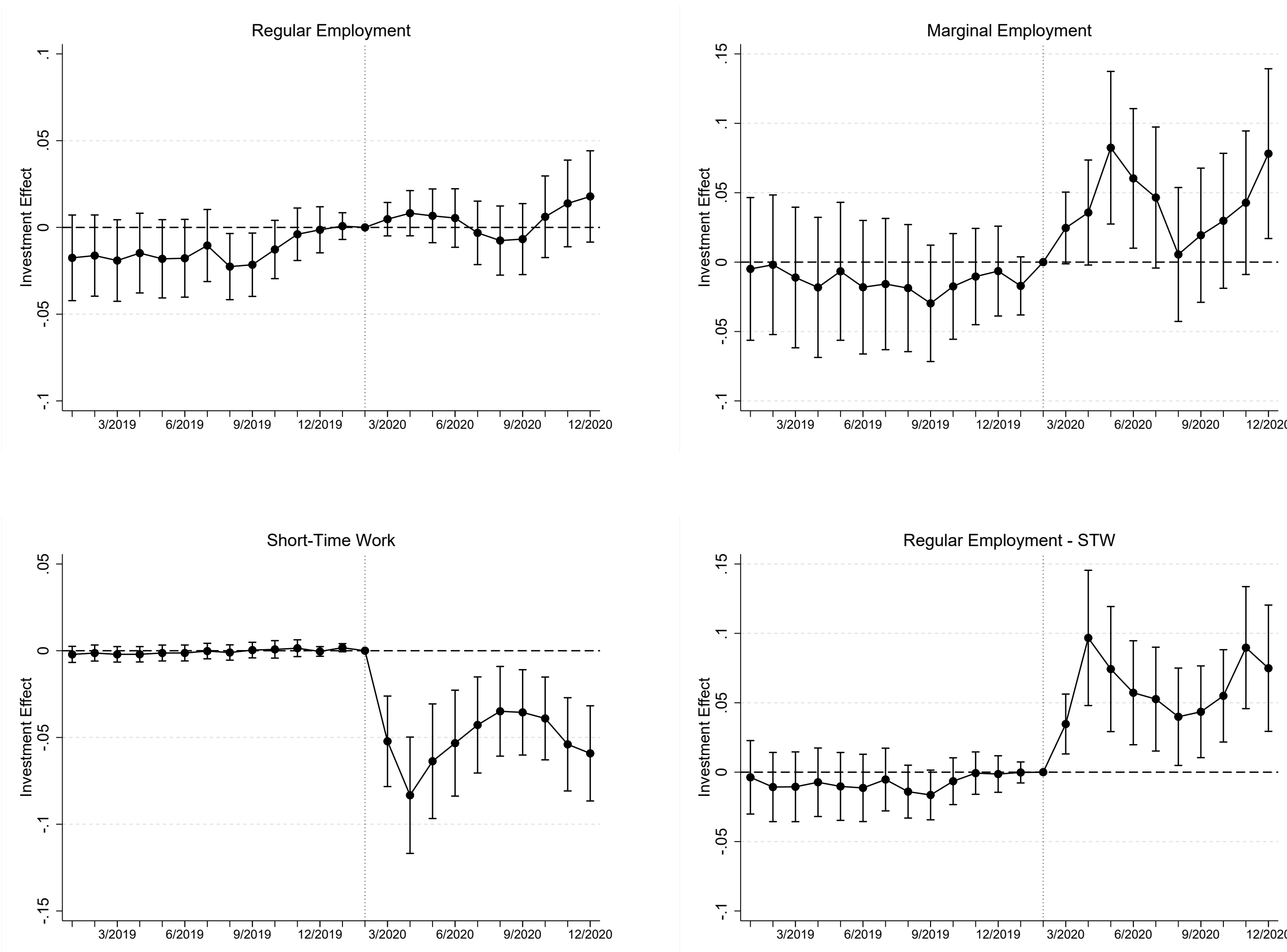


Notes: The graph shows the evolution of regular employment, short-time work, regular employees who worked their normal hours and marginal employment separately for investors and non-investors as well as their respective 95% confidence intervals (±2 SEs of the mean). Regular employment (shown in the top 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 that is not in short-time work (STW), defined as the number of regular workers minus the employment equivalent in STW[13]. Mean annual changes are shown for regular employment, marginal employment and regular employment working normal hours, while short-time work refers to the share of regular employees. The sample consists of 1,711 firms that we observe in the administrative data over the whole period.

change is however considerably more pronounced among non-investing firms.

To investigate the connection between investments in digital technologies and the different types of employment systematically, we re-estimate equations (4) and (5). Figure 7 shows event study plots for the four employment categories (regular employees, marginal employees, short-time workers and the number of regular employees not on short-time work) for investing firms relative to non-investing firms and controlling for time and firm fixed effects. 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. 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 where we see fewer layoffs and to regular employees who are less likely to work reduced hours.

Figure 7: Event Studies for Different Types of Employment



Notes: The graph shows the estimated β coefficients and 95 % confidence intervals from equation (5) controlling for time and firm fixed effects. For regular and marginal employment, the dependent variable is total (log) monthly employment. For short-time work, the dependent variable is the share of regular employees in short-time work. For regular employment not in short-time work the inverse hyperbolic sine (IHS) is used. The reference month is February 2020. Standard errors are clustered at the establishment level.

For the group of regular workers, the bottom right panel of Figure 7 considers the amount of employment not in short-time work, i.e. regular employment minus the employment equivalent in short-time work. The raw difference has a lot of zeros because many firms do not use short-time work in a given month. We therefore transform the the difference using the inverse hyperbolic sine. The graph suggests that investors have a 5-8% lower share of workers in short-time work. Accordingly, investing firms keep a larger share of their employees working regular hours than non-investing firms; the effect amounts to 5 to 6 percentage points[14].

The estimated relationships are summarized in Table 4. We first compare employment adjustments for different types of workers in investing firms compared to non-investing firms. In even columns, we split investing firms into firms that invested because of the pandemic and firms that invested independently of it. 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. If we zoom in on regular employees who are not in short-time work in column (3), 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 among investors that could already be seen in Figure 7.[15] Column (4) shows that this effect is primarily due to firms that invested *because* of the pandemic. The last two columns show that a similarly sized and statistically significant effect can be found for marginal employees. However, when we differentiate by the reason for the investment, we find that this effect applies to a similar extent to firms that invested because of or independently of the pandemic.

5.3 Robustness Checks

We perform a range of robustness checks to ensure that the differential employment performance in investing firms 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).

One concern is that some firms might have faced 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 x month x 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

[14]This measure of short-time work combines changes in short-time work (the numerator) with changes in regular employment in general (the denominator).

[15]We also use an alternative definition of regular employment 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 even larger, which makes sense as the average number of hours lost due to short-time work in the pandemic was about 50%.

Table 4: Investments and Different Employment Margins

	Regular Employment		Employment not in STW		Marginal Employment	
	(1)	(2)	(3)	(4)	(5)	(6)
Digital Investment	0.001		0.057***		0.056**	
	(0.011)		(0.018)		(0.026)	
Pandemic Investment		0.002		0.064***		0.051**
		(0.011)		(0.019)		(0.027)
Invested independently		-0.003		0.039		0.070**
		(0.018)		(0.027)		(0.034)
Firm FE	yes	yes	yes	yes	yes	yes
Time FE	year x month	year x month	year x month	year x month	year x month	year x month
Firm-specific Trends	yes	yes	yes	yes	yes	yes
No. Firms	1854	1854	1854	1854	1665	1665
Observations	65348	65348	65348	65348	53021	53021

Notes: The table shows regressions based on (4). The dependent variables are log regular employment in columns (1) and (2), regular employment minus short-time work (using the inverse hyperbolic sine transformation) in columns (3) and (4), and marginal employment in columns (5) and (6). 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 reference category are non-investing firms. All specifications include time and firm effects as well as firm-specific linear trends. Standard errors are reported in brackets and are clustered at the establishment level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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 in column (3) for year x month x industry fixed effects. Industries are defined by nineteen broad categories; the results remain unchanged. Alternatively, column (4) includes year x month x 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 report (very or moderately) negative effects and firms that reported no negative effects in the spring of 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 addition, we also control for year x month x industry fixed effects to account for the differential severity of shocks that industries experienced in the pandemic. The results show that even 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 favourable development of regular employment (net of short-time work). The effect on marginal employment is of a similar magnitude as in the baseline, but no longer 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 might perform better and have more favourable employment trajectories than non-investors because they have better financial resources or are more capable to compensate adverse shocks or are more resilient to absorb the economic costs without laying off workers. To check for the effects among better performing firms, we restrict the sample to firms in the top half of the firm wage premium distribution.[16] Investing firms are overrepresented in the sample of high-performing firms. Yet, column (7) shows that among those firms, investors are less likely to make use of short-term work schemes and more likely retain regular and marginal employees.

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 (8) of Table 5 thus restricts the sample to firms that report in the spring of 2021 having sufficient financial funds to keep their operations running. 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 find that investing firms have more favorable employment outcomes than non-investing firms. These additional tests provide additional 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.

Overall, the robustness checks show that the more favorable development of different employment outcomes of 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

Further, we analyze whether firms' employment adjustments differed depending on their investment intensity, their training activities or in which sector they operate. Table 6 reports results from our baseline specification for the share of employees in short-time work (Panel A), the number of regular

[16] See Section 2 for a description of this measure.

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) High 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***	-0.029**
	(0.012)	(0.012)	(0.012)	(0.011)	(0.018)	(0.007)	(0.016)	(0.014)
No. Firms	1854	1854	1854	1854	1002	850	1022	876
	Panel B: Regular Employment − Short-Time Work							
Digital Investment	0.057***	0.061***	0.052***	0.048***	0.079***	0.008	0.040*	0.042**
	(0.018)	(0.018)	(0.017)	(0.017)	(0.026)	(0.018)	(0.022)	(0.021)
No. Firms	1854	1854	1854	1854	1002	850	1022	876
	Panel C: Marginal Employment							
Digital Investment	0.056**	0.056**	0.053**	0.060**	0.046	0.048	0.074*	0.075**
	(0.026)	(0.026)	(0.026)	(0.027)	(0.037)	(0.034)	(0.039)	(0.037)
No. Firms	1665	1665	1665	1665	902	761	946	790

Notes: The table shows regressions based on equation (4), where all specifications include firm fixed effects, time (year x 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 firms reporting few or no adverse effects at the start of the pandemic. Specifications in columns (5) and (6) further include year x month x broad industry fixed effects. In column (7), the sample is restricted to firms in the top half of firm fixed effects. Finally, column (8) restricts the sample to firms that report facing no liquidity constraints. Again, the specification in column (8) controls for year x month x broad industry fixed effects. Standard errors reported in brackets are clustered at the establishment level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

employees net of those in short-time work schemes (Panel B) and marginal employment (Panel C).

We first split the sample of investors into moderately investing (investing in fewer than four digital tools) and heavily investing (investing in at least four digital tools) firms. Non-investors remain the control group in each case.[17] 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. Yet, firms that invested more heavily in digital tools had more regular employees working normal hours and reduced marginal employment less than firms that invested less extensively in digital tools.

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 as control groups. 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

[17] Figure 1 indicated that the median establishment invested in three digital tools. We use the investment scope to proxy for how much investing firms adjusted their workflow during the pandemic.

more likely to work normal hours and marginal employment declines less if the firm engaged in training their workforce to use digital tools than in firms that did not train during the pandemic.

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 keep up normal operations. In low-skilled services, digital tools can often not replace face-to-face interactions as business closures required employment 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 again include year x month x 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. It is thus particularly firms in the service sector where digital tools helped to cushion the workforce and vulnerable marginal employees from the severe shock of the pandemic recession.

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. There is little evidence that investing firms adjusted wages in response to declining demand or disruptions in production more or less than non-investing firms. We use our baseline specification in equation (4) 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 $\hat{\beta} = -0.007$ with a standard error of $S.E. = 0.012$. 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.

Rather than cutting wages during the pandemic, firms might have postponed wage increases instead. In January 2021, firms were asked whether they had postponed planned wage increases. About 30% of investing firms and an equal share of non-investing firms reported that they had indeed postponed wage increases.[18] In sum, despite the sizable disruptions of the pandemic, we see few adjustments in

[18]Here, the sample consists of about 900 firms that responded both to the wave in February of 2021 and the wave in

Table 6: Heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)
	$\leq$ 3 Investment Areas	$>$ 3 Investment Areas	Training	No Training	Manufacturing	Services
			Panel A: Share Regular Employees in Short-Time Work			
Digital Investment	-0.052***	-0.056***	-0.061***	-0.046***	-0.009	-0.070***
	(0.014)	(0.014)	(0.013)	(0.014)	(0.019)	(0.015)
No. Firms	1303	1226	1254	1269	515	1294
			Panel B: Regular Employment − Short-Time Work			
Digital Investment	0.038*	0.079***	0.085***	0.029	0.043*	0.054**
	(0.022)	(0.019)	(0.019)	(0.022)	(0.022)	(0.023)
No. Firms	1303	1226	1254	1269	515	1294
			Panel C: Marginal Employment			
Digital Investment	0.038	0.077***	0.071**	0.041	0.027	0.066**
	(0.029)	(0.029)	(0.028)	(0.029)	(0.045)	(0.032)
No. Firms	1147	1087	1111	1118	461	1167

Notes: The table shows regressions based on (4), 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 x 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 x month x broad industry fixed effects as well. The control group in column (5) and (6) are non-investing firms in manufacturing and services respectively. Standard errors reported in brackets are clustered at the firm level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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).

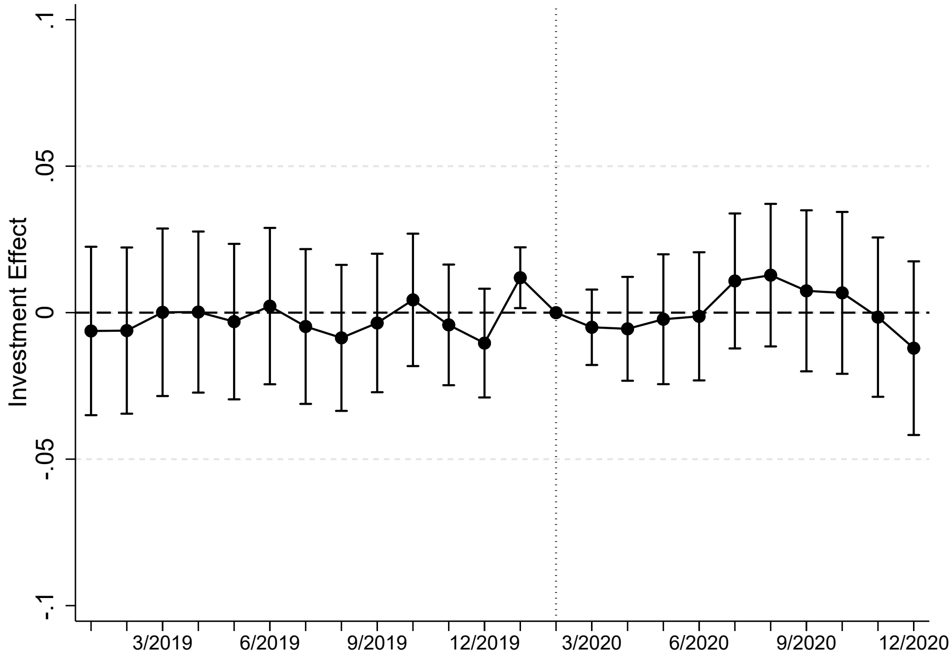
6 Employment Flows and Heterogeneity

6.1 Employment Flows

We have shown that employment dynamics during the pandemic differed substantially across firms 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 in 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 in 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

January of 2021.

Figure 8: Event Study Estimates for Wages



Notes: The graph shows the estimated β coefficients and 95%-CIs from model (5) with log (monthly) median wages as the dependent variable. The reference month is February 2020. The specification includes time and firm fixed effects. Standard errors are clustered at the establishment level.

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 (4). 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 less in investing firms though the coefficient is not statistically significant. More importantly, outflows in investing firms are significantly lower than in 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 even during the pandemic. As a result, firm retention as measured by netflows in column (3) are 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.[19] In Panel B, we find a very similar pattern as for total employment. Investing firms had smaller inflows of

[19]Information on short-time work is only available at the firm level, not for the individual employee. As such, we cannot study inflows and outflows for employees on short-time work separately.

regular employees than non-investing firms. At the same time, outflows of regular employees were much lower in investing firms than in 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 are weaker: inflows of marginal workers were reduced to a similar extent in 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)	(2)	(3)
	Inflows	**Outflows**	**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 regressions based on (4), where all specifications include firm fixed effects, time (year x 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, all firms might be more eager to keep their more skilled or more experienced workforce in order not to suffer a loss of human capital during the pandemic. However, we have shown that regular employees could be insured by STW, whereas marginal employees (who tend to be lower-skilled) could not. How investments affect the decision who to retain, who not to hire or who to layoff is not clear a priori. We thus analyze worker inflows, outflows and netflows for different skill groups, age groups and by gender. The results based on our baseline specification (4) are shown in Table 8. Panel A distinguishes between high-, medium- and high-skilled workers; Panel B reports results for young workers below age 30, prime-aged workers between the ages of 30 and 50 and older workers above age 50; and Panel C reports results for men and women.

Panel A shows the results by skill groups. Interestingly, investing firms are slightly less likely to hire high-skilled workers than non-investing firms (see 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 more 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 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 in 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 in 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, for instance. 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 towards the digital transition, how firms invested in training and how this impacted firm employment in Germany. Roughly two thirds of all establishments have invested in some form of 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,

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 β-coefficients based on (4), where all specifications include firm fixed effects, time (year x 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: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

firms in knowledge-intensive services and firms with a large share of high-skilled employees. Moreover, the possibility to have employees working from home is one important driver for updating the digital infrastructure.

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.

Finally, we 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 of their regular workers into short-time work, had more employees working normal hours and had to layoff fewer marginal workers than non-investing firms.

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 is strongly 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 reasons for non-investment*

   Why have you not made any investments in IT or digitalisation since the beginning of the Covid-19 crisis? Please state all the applicable reasons.

   (a) No investments were necessary
   (b) Investments would have been too costly
   (c) The planning and implementation would have involved too much work
   (d) The available internet speed does not permit further investments
   (e) The establishment lacks the staff to be able to carry out the investments in a suitable manner
   (f) We were unable to find a contractor to carry out the work for us

4. *Question on advanced digital technologies*

   Are the following technologies used in your establishment?

   (a) Software or platforms for production, sales or distribution, such as online shops or online crowdwork
   (b) Program-controlled equipment, such as robots, drones, CNC machines or 3D printers

(c) Advanced digital technologies, such as virtual reality, analysis of big data, machine learning or artificial intelligence

Since the beginning of the Covid-19 crisis, has your establishment introduced these technologies for the first time, expanded or reduced their use or left them unchanged?

5. *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?

6. *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?

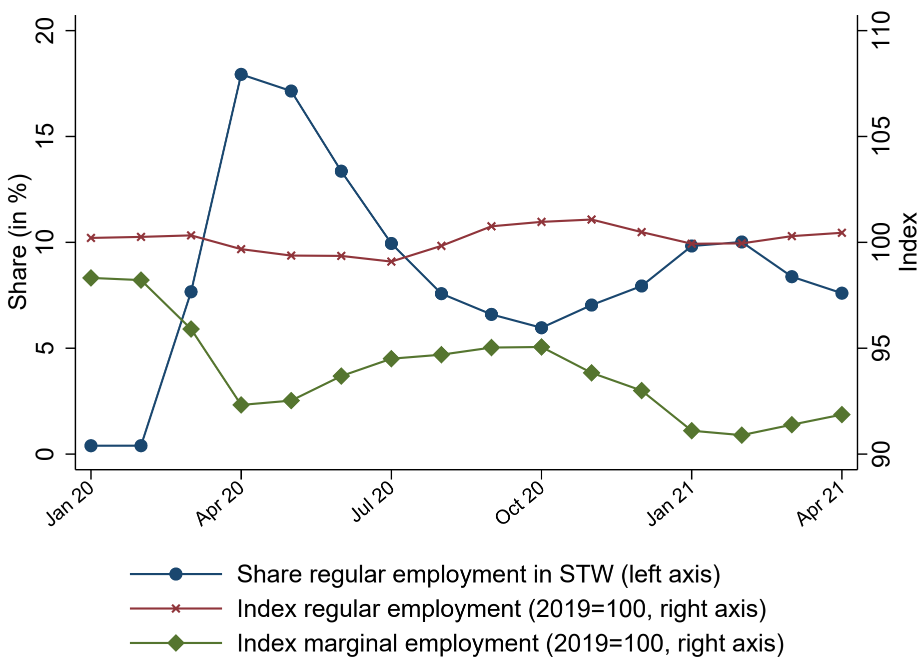
   (a) Skills in IT applications, e.g. Microsoft Office
   (b) Specialist IT knowledge and software programming
   (c) Communication and cooperation skills, also using digital communication media, such as Microsoft Teams, Skype or Zoom
   (d) Management skills, such as management from a distance
   (e)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

7. *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?

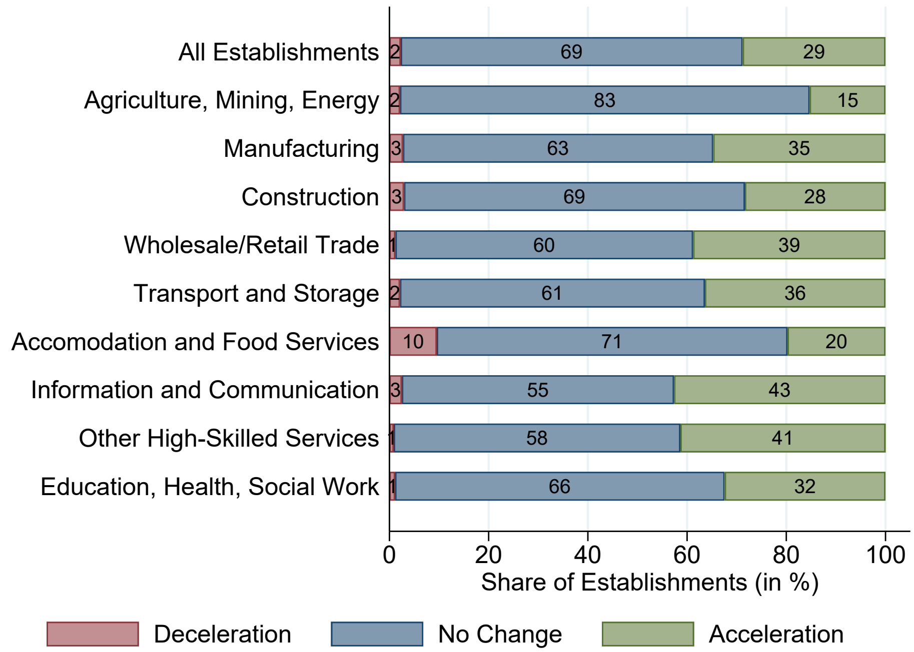
B Additional Results

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 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 2019 average values. Data on the employment type totals come from the Federal Employment Agency.

Figure A.2: Diffusion of Digital Technologies by Detailed Sectors



Notes: Shown are firms' assessments about how the COVID-19 pandemic has affected the diffusion of digital technologies in the firm. $N = 1,814$ establishments.

Table A1: Summary statistics

	Investment			Investment due to Pandemic		
	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)

	Investment			Investment due to pandemic		
	Yes	No	Difference	Yes	No	Difference
	(1)	(2)	(3)	(4)	(5)	(6)
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)
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***

	Investment			Investment due to pandemic		
	Yes	No	Difference	Yes	No	Difference
	(1)	(2)	(3)	(4)	(5)	(6)
	(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. In 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 where the dependent variables are indicators equal to one if an establishment 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: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$