// NO.24-057 | 09/2024

DISCUSSION PAPER

// MELANIE ARNTZ, MICHAEL J. BÖHM, GEORG GRAETZ,
TERRY GREGORY, FLORIAN LEHMER, AND CÄCILIA LIPOWSKI

Firm-Level Technology Adoption in Times of Crisis

Firm-Level Technology Adoption in Times of Crisis*

Melanie Arntz[1], Michael J. Böhm[2], Georg Graetz[3], Terry Gregory[4], Florian Lehmer[5], and Cäcilia Lipowski[6]

[1] *University of Heidelberg*

[2] *TU Dortmund*

[3] *Uppsala University*

[4] *LISER Luxembourg*

[5] *IAB Nuremberg*

[6] *Ifo Institute*

September 23, 2024

Abstract

This study investigates how crises affect firms' adoption of frontier technologies using the Covid-19 pandemic as a case study. The analysis tracks the nature, timing, and pandemic-related motivations of investments among German firms, using longitudinal survey data linked with administrative worker–firm records. We find clear evidence for a shift toward remote work technologies that helped firms mitigate negative employment effects. Overall, however, the pandemic slowed down the diffusion of new technologies. This procyclical pattern of technology adoption is particularly striking since the pandemic created strong incentives to experiment with new technologies.

Keywords: Firm-level technology investments, cyclicality of technology adoption, Covid-19 crisis

JEL codes: O33, E22, E32, J23

*Corresponding author: Georg Graetz (georg.graetz@nek.uu.se). Moritz Johanning, Joyce Käser, and Nick Niers provided excellent research assistance. We thank Christian Bayer, Wolfgang Dauth, Albrecht Glitz, Eva Mörk, Michael Oberfichtner, Oskar Nordström Skans, Daniel Tannenbaum, Martin Watzinger, as well as seminar participants at the AEA, IAB, LISER, UCLS, EALE, RES, ZEW, and the Universities of Trier and Hohenheim for helpful comments. All remaining errors are our own. This research was financially supported by the German Federal Ministry of Labor and Social Affairs (grant number DKI.00.00016.20), Forte grant 2021-01559, an IZA Collaborative Research Grant, the Leibniz Association through the Leibniz Professorship for Applied Labor Economics at the University of Heidelberg (P56/2017), Research Council of Norway grant 314801, and a WASP-HS grant.

1 Introduction

The diffusion of new technologies across firms is a key driver of long-run economic growth. Yet we know relatively little about how technology adoption interacts with the business cycle and how it is affected by crises. This question has important implications for our understanding of business cycle dynamics, labor markets, and the welfare consequences of recessions. In particular, while overall investment is strongly pro-cyclical, there are reasons to believe that investments in frontier technologies are not, and perhaps even grow faster during recessions. Studying this question empirically is demanding due to a host of confounding factors and scarcity of data on firm-level technology adoption over the cycle.

In this paper, we study the impact of the Covid-19 pandemic on firms' adoption of frontier technologies. The pandemic is a particularly intriguing case for investigating technology adoption during times of crisis: Many observers expected the pandemic to accelerate innovation given the unprecedented challenges it posed, including the urgent need for remote interaction among employees and with customers. However, assessing the causal impact of the pandemic on technological change comes with significant data and identification challenges. It not only requires detailed data on firms' technology investments, but also necessitates the construction of a credible counterfactual, given that the pandemic shock hit the entire economy.

We meet these challenges by leveraging novel data from a representative survey of German firms. In particular, we asked firms whether they invested in frontier technologies during the period 2016–2021; if so, when; and if they invested since the start of the pandemic, whether the investment was due to the pandemic.[1,2] Furthermore, we elicited the applications of the technologies that were installed. For quantification, we asked firms to report the frontier technology share among all the technologies they currently use, and how this share changed since 2016. Finally, a subset of respondents were part of a previous survey on technology adoption that we conducted in 2016.

Our first contribution is to document a set of new stylized facts about frontier technology adoption in the context of the Covid-19 pandemic. First, frontier office technology actually advanced more slowly during 2016–2021 than respondents in the previous survey wave expected. At manufacturing firms, the growth in frontier production technology nearly stalled. Second, a disproportionately large share of investment activity during 2016–2021 took place before the pandemic already. Third, a relatively small share of firms reported to have invested in frontier office technology due to the pandemic, and for production equipment this share is virtually zero. Fourth, among investments in office

[1] By frontier technologies, we mean technologies invented since the late 2000s that are self-controlled and fully integrated into firms' central IT system so that the work process is largely autonomous from human intervention. See Section 2 for more details.

[2] Strictly speaking, we surveyed establishments, but for brevity we use the term 'firm' throughout.

technologies due to the pandemic, those facilitating remote work were much more common than before the pandemic.

Our second contribution is to estimate the *causal* effect of the pandemic on frontier technology adoption. Estimating the causal effect of the pandemic poses a significant challenge, as it requires constructing a valid counterfactual. We attempt to do this via two distinct strategies. Following a growing literature on survey designs (Stantcheva, 2023, for instance), the first strategy leverages firms' responses about investments made *due to* the pandemic. Using the standard potential outcomes framework but assuming that all firms were assigned treatment, we argue that firms reporting investments due to the pandemic can be seen as *compliers*. Under reasonable assumptions, the growth in the frontier technology share among these compliers yields an upper bound on the pandemic's average treatment effect on the treated (ATT). Multiplied by the share of complier firms, this in turn yields an upper bound on the average treatment effect (ATE).[3] We achieve an upper bound rather than point identification for two reasons: Compliers are likely positively selected (for which we provide evidence), and we cannot identify firms that abandoned planned investments due to the pandemic (*defiers*). Our second strategy to gauge the causal effect of the pandemic on frontier technology adoption is to calculate a counterfactual scenario based on pre-pandemic investments. Here we exploit the timing of investments within the period 2016–2021 relative to the start of the pandemic. As a variant on our second strategy, we also calculate a counterfactual scenario based on pre-pandemic investment plans.

Our evidence strongly speaks against the hypothesis of a crisis-induced push in technology adoption (*crisis push*), the notion that the pandemic caused an acceleration of technological progress. The first strategy yields an upper bound on the average treatment effect (ATE) of a 0.5 percentage points (pp) increase in frontier technology shares, a small fraction of the average increase during 2016–2021 (3.0pp). Turning to the second strategy, we document that investments made between 2016 and March 2020 led to substantial increases in frontier technology shares. Simple extrapolation for the time of the pandemic implies that these shares should have increased by 50 percent more than they actually did. A counterfactual scenario based on the investment plans reported in 2016 yields an even higher counterfactual increase. Therefore, our second strategy suggests a negative ATE of the pandemic on frontier technology adoption. Specifically, we observe a decline in investments that is equivalent to losing 1.4 years' worth of investment activity during normal times. There is also no evidence at this point that the pandemic will trigger a delayed acceleration in technology adoption in the medium run: Firms that did invest during the pandemic do not have more ambitious plans for 2021–2026 than other firms.

[3] We also consider that firms may have been exposed to varying degrees to the pandemic. However, even a rich set of exposure metrics has little predictive power for investment patterns.

Instead of a crisis push, our findings align more with an alternative hypothesis of a crisis-induced shift in technology adoption (*crisis shift*): The pandemic prompted firms to reorganize in order to adapt to changed circumstances and especially to facilitate remote interaction. Our third contribution is thus to document a crisis-induced shift in the applications of new technologies, and to explore whether this response helped firms mitigate the adverse employment effects of the pandemic. Our data reveal increased investments in remote work technologies at the expense of other frontier technologies. Of frontier office investments made due to the pandemic, more than 50 percent facilitated remote work, compared to just over ten percent of pre-pandemic investments. In contrast, while technologies facilitating management, product design, and planning accounted for more than ten percent of pre-pandemic investments, their share dropped to about one percent among investments made due to the pandemic. This shift in the applications of new technologies allowed firms to mitigate the adverse employment effects of the crisis. Firms reporting investments due to the pandemic made greater use of remote work, had a lower incidence of subsidized short-time work, and saw overall employment contract less. Thus, in adapting their technology mix to pandemic circumstances, firms may not have achieved an acceleration of technological progress, but were better able to shield their workforce from the pandemic-induced recession.

This paper relates to three strands of the literature. First, using detailed firm-level evidence, we add to the understanding of technology investments during crises and recessions, which has potentially important implications for the welfare effects of the business cycle (Cerra et al., 2023). In particular, a set of papers have shown that investments in research and development (R&D) are much less cyclical (or even counter-cyclical) than aggregate investments or investments in physical capital (Aghion et al., 2012; Bloom, 2007). At the same time, recent research in labor economics has found that the effect of technological change on workers and jobs seems to accelerate during economic crises (Hershbein and Kahn, 2018; Jaimovich and Siu, 2020). This suggests that also the adoption of new technologies—which partly overlaps with R&D, partly follows it through diffusion[4]—may be acyclical or even counter-cyclical.

Compared to R&D, evidence on the cyclicality of frontier technology adoption is scarce. Our findings suggest that technology adoption may behave more like aggregate investment than R&D, slowing down during crises. This represents another, previously less recognized, adverse effect of crises. We further identify a shift in the applications of technologies adopted, toward technologies that help firms cope with the crisis, but which are also less substantial and less consequential for technological progress. Together, our findings are consistent with theories of directed technical change (Acemoglu et al., 2012; Newell et al., 1999) but also with option value theories of investment wherein firms opti-

[4]Bryan and Williams (2021) argue that, since few firms engage in R&D, most social value of innovations derives from their diffusion to other firms and final users.

mally prefer to wait and see instead of making potentially irreversible investment decisions under heightened uncertainty (Benhabib et al., 2014; Bloom et al., 2007).[5]

Second, our paper contributes to the literature on technology diffusion. It is closely related to recent work on the diffusion of current frontier technologies, especially as elicited through firm-level surveys (Acemoglu et al., 2022; McElheran et al., 2022; Zolas et al., 2020; Genz et al., 2021; Arntz et al., 2024), as well as to an older literature on technology diffusion (Acemoglu and Restrepo, 2022; Bloom and Van Reenen, 2007; Griliches, 1957).[6] We advance this literature by exploring the role of an aggregate shock—the Covid-19 pandemic—in the adoption of frontier technologies.

Finally, our paper contributes to the debate about whether Covid-19 accelerated technological change. Several pandemic-related innovations[7] as well as the sharp rise in working from home (Barrero et al., 2023) and in digital interactions (Avalos et al., 2023) have been taken to indicate an acceleration of technological progress in response to the crisis (LaBerge et al., 2020; Valero et al., 2021). Two papers study the role of the Covid-19 pandemic in firm-level technology adoption, which is also our focus. Barth et al. (2022) report that Norwegian firms adopted new technology because of the pandemic. Gathmann et al. (2024) find that 50 percent of German firms invested in digital technologies due to Covid-19, interpreting this finding as evidence for a "pandemic push". We are able to provide a more nuanced picture as our data allow us to assess pre-trends in technology adoption, to construct counterfactual scenarios, and to distinguish between more and less impactful investments.[8] Drawing on these data and identification strategy, we find that while the pandemic substantially increased investments in remote work, many of these investments were secondary in importance and did not suffice to raise the overall pace of frontier technology adoption. Our results thus contradict the notion of a push in technology adoption but support the finding that Covid-19 affected the direction of technological progress toward technologies that support working from home (Bloom et al., 2021).

The paper proceeds as follows. Section 2 describes our novel firm-level data and provides baseline descriptive statistics. Section 3 develops two hypotheses about the impact of the pandemic on technology adoption, one positing a crisis-induced push in technology adoption, and the other positing a shift. Using a potential outcomes framework, the section further explains how our unique data can be leveraged to evaluate these hypotheses.

[5]A Covid-specific reason for the slow-down may be that disruptions and lockdowns due to the pandemic could have made it harder to implement new technologies. In our data, however, we find no association between firms' Covid exposure and technology investments. For further discussions of the specificity of Covid and merits of case studies in crisis research more generally, see Sections 3 and 6, respectively.

[6]Part of our analysis focuses on the relationship between adoption of current frontier technologies and labor demand, similar to for instance Acemoglu et al. (2020); Bessen et al. (2020); Gaggl and Wright (2017); Koch et al. (2021).

[7]Innovations were for example in areas such as mRNA vaccines, contact tracking, air purification, or mass online learning; see also `https://www.covidinnovations.com/`.

[8]Gathmann et al. (2024) include all digital investments whereas we focus exclusively on frontier technologies, consistent with recent studies of technology diffusion.

Section 4 presents our results related to the crisis push, while Section 5 does the same for the crisis shift. Section 6 concludes.

2 Linked survey–administrative data

Our dataset links a survey of firms' technology investments to administrative data on all employees at the surveyed firms, and to official data capturing exposure to the pandemic.

2.1 Firm-level survey of technology adoption

From October 2021 to July 2022, we conducted a representative survey of technology adoption among German establishments (plants or operating sites, henceforth *firms*). The survey constituted the second wave of the IAB-IZA-ZEW Labor Market 4.0 Establishment Survey (BIZA II). The first wave (BIZA I) took place in 2016 and we discuss its link to the current survey in more detail below. The 3,003 firms that participated in BIZA II are a stratified random sample of all German establishments with at least one employee subject to social security contributions, covering both private and public sectors.

Sampling and implementation. Our survey was stratified by industry, firm size, and federal state. To correct for over- and under-sampling, we weight observations in most of our calculations with the inverse probability of being in a specific stratification cell of the survey sample (hereafter referred to as firm stratification weights). These weights make our results representative of the population of German firms.[9] See Section 2.3 below and Appendix B.1 for details on representativeness and non-response.

We designed the questionnaire in collaboration with a professional survey company, adapting the BIZA I questionnaire to the context of the Covid-19 pandemic. The survey company implemented the survey via computer-assisted telephone interviews with staff knowledgeable about the firm's technology use (production or general managers).

The median interview date of BIZA II was April 1, 2022 (see Figure B1 for the distribution of interview dates). Given that the pandemic officially reached Europe in late February 2020, our survey on average covers a Covid-19 period of well above two years. When asked about past technology use, the vast majority of participants referred to values from 2016. We label our analysis period "five-year period 2016–2021". Note that this period is likely longer than five years, assuming that responses about past technology use referred to mid-2016.

[9] We re-calculate key results using employment-adjusted weights (multiplying the firm stratification weights by employment) to see how the picture emerging from the firm-weighted results compares to the experience of the typical German employee.

Technology use by level of sophistication. The survey presented respondents with a conceptual framework classifying firms' work equipment into three levels of sophistication corresponding to distinct phases of technological progress. This framework was introduced by Genz et al. (2021) and Arntz et al. (2024) for BIZA I. The classification aims to be as general and comparable across firms and time as possible while at the same time allowing respondents to easily categorize the specific technologies they use. Therefore, the framework distinguishes technologies by level of sophistication and by broad area of application, namely office and communication equipment (*office* in short) and *production* equipment. We asked all firms to characterize their office equipment but naturally inquired about production equipment only at manufacturing firms.

Table 1 introduces our conceptual framework along with examples. The lowest technology level, *manual* technologies, refers to work equipment based on technologies that are typical for the First and Second Industrial Revolutions (before the Digital Revolution).[10] These include office equipment that is not IT-supported (for instance, an analog telephone or copy machine) and manually controlled production equipment (for instance, a drilling machine). Work equipment based on *digital* technologies reflect the computerization wave of the Third Industrial Revolution (First Digital Revolution) that started in the 1970s and enabled IT-based automation of specific sub-processes. This category consists of IT-supported office (for instance, a personal computer) and indirectly controlled production (for instance, a CNC machine or industrial robots) equipment.

The highest technology level, *frontier* technologies, refers to the Fourth Industrial Revolution (Second Digital Revolution) since the late 2000s. Work equipment belonging to this category is self-controlled and fully integrated into the firm's central IT system so that the work process is largely autonomous from human intervention. Examples for IT-integrated office equipment are cloud computing or automated marketing such as tools for targeted communication and customer relationship management systems. Examples for self-controlled production equipment include manufacturing execution systems, which coordinate machines on a centralized software platform in real time, or smart robots with advanced sensors, connectivity, and dynamic data processing capabilities. Here we are interested in the diffusion of new technologies and in technological progress at the frontier, similar to other recent studies using survey data as reviewed in the introduction. Therefore, we focus the subsequent analysis on the top level of our classification, and thus on firms' adoption of frontier technologies.

We presented respondents with a one-paragraph explanation of our framework including examples. We then asked them to estimate what share of office and production equipment belongs to each of the three technology levels, respectively, what the distribu-

[10] The First Industrial Revolution (starting around 1760) marks the transition from hand production to the wide-spread use of machines powered by water and steam. The Second Industrial Revolution (starting in the late 19th century) saw the introduction of electricity-powered mass production and assembly lines.

tion was in 2016, and what they expect it to be five years into the future. In the remainder of the article, we will refer to the share of office and production equipment that companies associate with the highest technology level as the frontier technology share.

Specific technologies and AI use. The survey continued by asking firms to name the most important frontier technology investment that they made during the past five years, if any. We also asked firms to name further frontier investments, especially in relation to the pandemic—see next paragraph. We use all responses to classify investments into different applications when assessing the hypothesis of a crisis-induced shift in technology adoption in Section 5. The answers also tell us how respondents interpreted the highest level of technological sophistication as described in our framework. Examples for office equipment that firms mentioned include those listed in Table 1 as well as software for big data analytics, enterprise resource planning systems for data-based integration of different work processes, or intelligent productivity tools that feature coding and writing copilots as well as automated translation, transcription, and workflow support. Further examples that were mentioned for production equipment include autonomous warehousing, self-assembling machines, or 3D printers. We also followed up asking whether the technology invested in involves artificial intelligence (AI).[11] Among frontier investments in office technology, 26 percent involve AI, while for production equipment the figure is 11 percent. Given the technologies mentioned and the incidence of AI, we consider the survey responses to capture our intended concept of frontier technology quite well.

Main and secondary investments in frontier technologies. As mentioned above, we asked firms to name the most important frontier investment that they made during the past five years, if any. For this *main* investment, we then asked whether it was done during the pandemic (March 2020 or later), and if so, whether the investment was made because of the pandemic. This allows us to classify all main investments in frontier technologies into the mutually exclusive categories of *before*, *during but not due to*, or *due to* the pandemic.

After eliciting information on the main investment, we followed up asking whether the firm also conducted further, *secondary* frontier investments. In particular, if the main investment took place before the pandemic, we asked whether there was another frontier investment since the start of the pandemic, and if so, whether it was done because of the pandemic. If the main investment was made during but not due to the pandemic, we asked whether there was another investment due to the pandemic. If the main investment was made after the start of the pandemic, we asked whether another investment was made

[11] Our questionnaire defined AI as technologies that are based on machine learning and that are capable of classification, evaluation, or real-time decision making. The questionnaire further listed some common AI applications.

before the pandemic. These questions on secondary investments were thus conditional, and they were designed to maximize the detection of potential positive pandemic effects on investment activity.[12] This structure of our questionnaire results in a categorization of firms according to main and secondary frontier investments as shown in Table 3, to be discussed below.

Exposure to the pandemic and remote work potential. The pandemic created various impediments to businesses' operations, including social distancing, uncertainty, actual infections and illnesses, drops in demand, and problems in supply chains. We use indicators from the survey itself and from official sources to capture such different impediments. In the survey, we elicited: how many weeks the firm was forced by the government to cease operations; perceptions of uncertainty about the further course of the pandemic; changes in product demand and revenues; whether the firm applied for Covid-19 government support; and whether it had been affected by supply chain bottlenecks for frequently used primary and intermediate products. From official sources, we collected the Covid-19 hospitalization rate in the firm's local area. We obtain revenue growth in the firm's two-digit industry from a commercial data provider (Bureau van Dijk).[13]

As remote work was an important response to social distancing and related challenges during the pandemic, we also use measures of remote work potential and actual incidence of remote work in our analysis. Our *remote work potential* (RWP) index is constructed based on the firm's occupational composition in 2019 (using administrative employment data discussed below) in conjunction with Bruhns et al. (2024)'s RWP index, which assesses the potential to work from home for each detailed five-digit occupation. Our index takes values between zero and one and may be interpreted as the share of tasks that can be performed from home. In the survey, we directly ask about the increase in the share of the firm's employees working form home at the time of the interview as compared to before the pandemic. See Appendix B.2 for more details.

Sample of panel firms from BIZA I. The first wave of the BIZA survey was conducted in 2016, employing the same framework as BIZA II for measuring technology use by level of sophistication (see Table 1).[14] Of the original BIZA I firms, 465 participated

[12] Despite the conditional nature of these questions, they yield nearly complete information—whether or not an investment was made—in terms of the main/secondary margin and the pandemic timing/motivation margin. The exception is that in some cases we cannot rule out that a firm made a secondary investment during but not due the pandemic. However, by switching on the 'during-not-due-to' dummy in such cases, we can easily check the robustness of our results to these potentially unobserved investments.

[13] These data are the source for German firms in the ORBIS-AMADEUS database discussed by Gopinath et al. (2017).

[14] BIZA I can be accessed via the Research Data Center of the German Federal Employment Agency at the Institute for Employment Research (IAB), see `https://fdz.iab.de/en/our-data-products/establishment-data/biza/`.

in the BIZA II survey. Matched across survey waves, these firms constitute our *panel sample*. In addition to the main variables from above, this sample contains firm-level information on technology shares of the firms' office and production equipment at the time of the BIZA I survey in 2016, retrospective information on technology shares five years earlier in 2011, and prospectively as then planned for 2021. We use BIZA I and the panel sample to measure longer-run technology trends, contemporaneously reported shares in 2016, and counterfactual technology shares (investment plans) for 2021. All calculations using the panel sample are based on firm stratification weights that are further adjusted to ensure the sample is representative of the population of German firms that exist both in 2016 and in 2021.[15]

2.2 Administrative employment and short-time work data

We link our survey firms to administrative labor market data provided by the Institute for Employment Research (IAB), thereby obtaining the full employment biographies of all employees liable to social insurance contributions in the surveyed firms during 2016–2021. This results in annually more than five hundred thousand unique individuals with, among others, information on daily wages, education, industry, and occupation.

We use this information to calculate the change in firm-level employment for the years 2019–2021, and to construct firm-level variables serving as controls in our regressions. In particular, we compute workforce composition by education (3 categories) and job requirement level (4 categories). We further use the IAB data to determine firms' industry (10 categories), size (4 categories), and location (16 federal state dummies, urban/rural region). Additionally, we match estimated firm fixed effects from Bellmann et al. (2020) as a measure of firm-specific wage premia, which is an update of Card et al. (2013) for more recent periods to our sample of firms.

Finally, we obtain administrative information on firms' usage of short-time work. This is based on their invoices to the federal employment agency to pay out short-time work allowances for economic or seasonal reasons. For detailed information on these labor market data, see Appendix B.3.

2.3 Descriptive statistics and representativeness

Table 2 presents summary statistics for selected characteristics of our sample of firms weighted with standard stratification weights. We are able to identify 2,985 out of the 3,003 BIZA II firms in the administrative data (column (1)). Due to missing information

[15]We do not study firm exit in this paper. Exit rates were not markedly different during the pandemic than in the years prior. For example, of firms operating in mid-2016, 16.6% had exited by mid-2018. For 2018–2020 and 2020–2022, the figures were 18.3% and 17.9%, respectively. The high level of government support during the Covid-19 crisis (German Ministry of Finance, 2020; German Ministry of Economic Affairs, 2022) likely mitigated any surge in exits.

on technology shares and investment choices, the sample further shrinks to 2,268 firms (column (2)). Comparing the two samples, we find that the distributions of size, sector, and share of firms in the East of the country are very similar.[16] Furthermore, we have verified that the survey sample of 2,985 firms is indeed representative of the entire population of firms in Germany (see Table B2).

Table 2, columns (2) and (3), also report means and standard deviations of key conditioning and shock variables including pandemic exposure, initial technology shares, remote work, employee characteristics, and firm fixed effects. Changes of technology shares and investment behavior are outcomes of our analysis and explored in depth below.

The last columns of Table 2 condition on the panel sample of firms with information from both BIZA I and II. Although the sample declines to just under 400 firms, means and standard deviations in this subsample are again similar to the main sample (other than somewhat lower shares of university graduates and expert job levels in the panel sample). This suggests, and later analyses corroborate, that even the panel sample is broadly representative of the population of firms in the German economy.

3 Hypotheses and empirical strategy

In this section we discuss our hypotheses about the effects of the Covid-19 pandemic on frontier technology adoption. We also explain how our survey data can be used to test these hypotheses, and in particular, what assumptions are needed for a causal interpretation.

3.1 Hypotheses about the pandemic and technological progress

In the following, we draw on existing research to frame two primary hypotheses that offer different perspectives on the relationship between the pandemic and frontier technology adoption. These hypotheses—which are not mutually exclusive—posit a crisis-induced push and a crisis-induced shift in technology adoption, respectively.

Crisis-induced push in technology adoption (crisis push). This hypothesis posits that Covid-19 accelerated the adoption of frontier technologies, in contrast to a scenario in which technology adoption is pro-cyclical. The hypothesis takes inspiration from studies on research and development (R&D). Frontier technology adoption partly overlaps with R&D, partly follows it through diffusion, so that the R&D literature may contain relevant lessons.

[16] Of the 2,268 firms, 1,623 have information on all our control variables. We impute values for the remaining firms based on sector and firm size. We do not impute technology shares or investment choices. Our results are robust to dropping firms with imputed values.

In contrast to investment overall, which is strongly pro-cyclical, R&D appears acyclical or perhaps even counter-cyclical (Aghion et al., 2012; Bloom, 2007). One theoretical explanation for this is that in light of reduced opportunity costs, firms should find it optimal to implement new technologies during recessions (Aghion and Saint-Paul, 1998; Francois and Lloyd-Ellis, 2003). This explanation is consistent with evidence suggesting that routine-biased technical change—that is, technological advancements that disproportionately affect routine tasks—has accelerated during recent recessions (Hershbein and Kahn, 2018; Jaimovich and Siu, 2020). Another reason against pro-cyclicality of R&D is that firms are less likely to make significant changes in their R&D spending under high uncertainty—a "caution-effect"—rendering it more persistent over the economic cycle (Bloom, 2007).

However, there are also reasons to expect a pro-cyclical behavior of new technology investments. Existing theories, again in relation to R&D, conjecture declining R&D investments in recession when firms are financially constrained (Aghion et al., 2010), as was the case during the Great Recession (Campello et al., 2010). Option value theories of technology diffusion suggest that firm would cut down irreversible, and potentially more substantial, investments when uncertainty rises during crises (Benhabib et al., 2014; Bloom et al., 2007). Finally, firms may invest more during upturns if there are benefits of own productivity improvements that in the long term also accrue to others, such that firms excessively weigh the higher short-term payoff to investment in a boom (Barlevy, 2007).

In the context of the pandemic, credit constraints might have been weaker than in other recent recessions due to government support,[17] whereas the need to implement new technologies may have been stronger. Another view suggests that disruptions and lockdowns due to the pandemic could have made it harder to implement new technologies. However, we find no association between firms' Covid exposure and investments in our data (see Appendix D). Finally, there is substantial evidence that the Covid-19 pandemic was indeed a severe uncertainty shock (Altig et al., 2020; Morikawa, 2021).

Overall, we might therefore expect the following patterns under a crisis push: First, firms should report that a substantial number of main technology investments were made due to Covid-19. Second, investments due to the pandemic should be associated with substantial increases in firms' frontier technology shares. Third, theories of endogenous technological change in which an increase in the stock of knowledge raises future returns to R&D (Romer, 1990b; Aghion and Howitt, 1992), suggest that investments due to the pandemic may raise firms' planned long-run technology adoption, too.

[17] While credit constraints greatly affected investments during the global financial crisis (Campello et al., 2010), government capitalization and liquidity provisions to firms were very generous during the pandemic (German Ministry of Finance, 2020; German Ministry of Economic Affairs, 2022).

Crisis-induced shift in technology adoption (crisis shift). This hypothesis posits that the pandemic led to a shift in the direction of technology investments and, in particular, that firms reallocated investments toward remote work technologies in order to maintain operations. This view is based on the fact that social distancing during the pandemic required remote interaction among employees and with customers, which led to a sharp rise in working from home (Barrero et al., 2023; Bick et al., 2023). The hypothesis implies that, to cope with the immediate impact of the pandemic, companies adopted specialized technologies that enable remote work and virtual collaboration. Bloom et al. (2021) also find evidence for a shift in patents toward remote work technologies during the pandemic. The crisis shift relates more generally to theories of directed technological change (Acemoglu, 2002; Acemoglu et al., 2012).

At the same time, one might expect technology adoption under the crisis shift hypothesis to constitute rather marginal or secondary investments compared to more substantial main investments. Empirical research has found that specific shocks may change the direction but not necessarily the overall rate of innovation (Newell et al., 1999).[18] In the particular case of remote work technologies, it is plausible that these required relatively minor expenses and could be implemented—or later reversed—on relatively short notice.

Under a crisis shift, we can thus expect the following adjustments among firms during the pandemic crisis: First, we expect a shift toward specific technology applications that enable working from home. Second, in contrast to the crisis push hypothesis, we would not be surprised if these technologies typically represent secondary investments rather than what firms consider the main investment during the 2016–2021 period. If so, these pandemic-induced investments will have less impact on overall firm-level technology adoption and trigger less follow-up investments in the future. Third, firms that introduce frontier technologies during the crisis should raise their actual rates of working from home, thereby stabilizing firm-level output and regular employment (instead of extensively relying on short-time work schemes).

Finally, we note once more that the crisis push and crisis shift hypotheses are not mutually exclusive, since the pandemic could simultaneously push firms toward more frontier technology investments while also shifting some focus toward remote work technologies.

3.2 Empirical strategy

The above hypotheses are challenging to evaluate empirically. They involve an aggregate shock hitting all firms, and suggest nuanced responses in terms of firms' technology in-

[18] Barrero et al. (2021) argue that working from home will stick after large-scale experimentation during the Covid-19 pandemic. Already before the pandemic, Bloom et al. (2015) studied a firm that experimented and then stuck with working from home. Working from home technology may also be relatively mature following the pandemic and not require extensive future investments.

vestments, requiring data on both sophistication and application of the new technologies installed. Our novel survey data meet these requirements and provide high-level descriptive evidence that serves as a first indicator for the relative merits of the crisis push and crisis shift hypotheses. For instance, we will compare the aggregate change in frontier technology shares 2016–2021 to the change in the previous five-year period as well as to firms' plans as stated in 2016. Thanks to the design of the survey we can go further and identify, at least in terms of bounds, the causal effect of the pandemic on frontier technology investments.

We now discuss the key terminology and intuition, while Appendix C contains the formal derivations. We combine advances from recent research on survey design and interpretation with the standard potential outcomes framework, which we modify in that we consider all firms to be assigned to treatment—the pandemic is an aggregate shock. The goal is to estimate the average treatment effect (ATE) of the pandemic on changes in frontier technology shares 2016–2021, which the crisis push predicts to be positive.

Our focus is on the comparison between firms that invested due to the pandemic (*compliers*) versus those that did not (*never takers*).[19] We assume that those investments which firms report to have made 'due to the pandemic' would not have been conducted in the absence of Covid-19. In other words, we assume that our survey respondents (at least implicitly) share our definition of causality. This assumption allows us to directly observe the compliers. Our approach follows a growing literature that has argued for surveys as providing identifying information (for example, see Roth and Wohlfart, 2020; Wiswall and Zafar, 2021; Stantcheva, 2023, among many others).

Observing the compliers in our data, we can potentially estimate the average treatment effect on the treated (ATT) of the pandemic by comparing the change in the frontier shares of compliers to the change among never takers. The latter group includes all firms who did not report having made any investment due to the pandemic, including those that invested during the pandemic but for other reasons. The group also includes firms that abandoned some investment plans due to the pandemic (*defiers*), which unfortunately we cannot identify in our data.

The estimated ATT multiplied by the share of compliers yields an upper bound on the average treatment effect (ATE) of the pandemic on the change in frontier technology shares. The upper bound arises for two reasons. First, there may be selection into complier status in the sense that these firms would have experienced higher technology growth even in the absence of the pandemic. In other words, our estimate of the ATT is upward-biased. We obtain evidence for such positive selection from investment plans reported in 2016. Second, the effects of the pandemic among the never takers as well as

[19] Adopting the terminology from instrumental variables is useful even though the analogy is imperfect. One may think of the occurrence of the Covid-19 pandemic as a binary instrument that is switched on for all firms.

among the defiers are plausibly non-positive.[20] These effects are needed to calculate the ATE but are impossible to observe. The non-positivity assumption however allows us to bound the ATE.

A second identification strategy allows us to gauge the importance of defiers based on the change compared to actual pre-pandemic investments. In particular, we measure the rate of frontier investments from 2016 to early 2020 and extrapolate it to the pandemic in order to compare it to the realized investments during that period. This strategy thus exploits the timing of investments, as they change from before versus after the start of the pandemic. Using our panel firms, we also create a counterfactual using their pre-pandemic investment plans.

We test the crisis shift hypothesis using our detailed data on the applications of newly installed frontier technologies, their timing, and reason. For instance, we compare the incidence of remote work technologies among investments made due to the pandemic to their incidence among investments before the pandemic.

Finally, while our framework treats the Covid-19 pandemic as an aggregate shock—hitting all firms and allowing for heterogeneous effects on frontier technology adoption—it is worth noting that there are two aspects of heterogeneity which the framework does not separate. First, firms may differ in how hard they are hit by the pandemic—they may experience different levels of exposure. Second, for a given level of exposure, firms may respond heterogeneously. We attempted to disentangle these aspects using observable variables such as pre-pandemic work arrangements, regional infection rates, and sectoral demand shifts, among others, but there turn out to be no robust predictors of changes in investment patterns (for the detailed analysis, see Appendix D). While a heterogeneity analysis based on observables is thus not the focus of this paper, such an analysis is also not necessary to gauge the overall effect of the pandemic on technology adoption.

4 Evidence on the crisis push hypothesis

We begin by providing evidence on the crisis push hypothesis, that is, whether the Covid-19 crisis accelerated the adoption of frontier technologies.

Section 4.1 gives an overview of the changes in frontier technology shares in office and production equipment over time. Section 4.2 documents the share of complier firms and their pace of technology adoption compared to never takers as well as decomposes the overall changes into the contributions of firms investing before, during, and due to the pandemic. Having presented these novel stylized facts, Section 4.3 then estimates the effect of the pandemic on the compliers' technology shares in regression analyses, also shedding light on potential selection bias using information on pre-pandemic plans.

[20] The effect of the pandemic among the never takers is likely zero, though we do not exclude the possibility that they were induced to invest more in older technologies.

Finally, Section 4.4 uses the estimated ATT and the share of complier firms to compute an upper bound on the overall effect of the pandemic on frontier technology adoption. Using pre-Covid investments and pre-period investment plans, it also gauges the extent of lost technology adoption which arises from canceled projects (defiers) due to the pandemic.

4.1 The evolution of frontier technology shares

Figure 1 shows actual and planned changes in frontier technology shares for three five-year periods, using both the 2016 and 2021 waves of our survey. The actual change is the difference between the current share and the share five years prior, the latter being based on respondents' recollections. Between 2011 and 2016, the data reveal an increase of 2pp since 2011 for office equipment, compared to 1.4 for production. Between 2016 and 2021, a period also covering the pandemic, we find larger increase for office equipment at 3pp point, whereas production equipment increased at only half the pace compared to the previous five-year period.[21] Planned changes for this period were also substantially larger than actual changes. Back in 2016, respondents had expected an increase in the frontier technology share from 2016–2021 of 5.6pp for office, and 2.8 for production. Expectations for the period 2021–2026 are similarly optimistic.

Hence, we see no broad acceleration in the adoption of frontier technologies during our period, and actual changes fell short of plans. This is already suggestive evidence that there was no pandemic push across the board, and we will come back to the evidence shown in Figure 1 later when we estimate the overall net effect of the pandemic based on extrapolating past trends and plans. At the same time, aggregate investment trends are foremost descriptive as, among other things, the observed shifts between 2016 and the survey date in 2021/2022 cover a period both before and after the Covid-19 shock. Therefore, we next focus on the variation within this period to document the investments made before the pandemic, during, and due to it. If there was a pandemic push, the share of compliers should be large and they should exhibit substantially faster frontier technology adoption.

4.2 The incidence of frontier investments before, during, and due to the pandemic

For both main and secondary investments that firms made during 2016–2021, we know whether they occurred 'before', 'during but not due to', or 'due to' the pandemic. Table 3 reports the share of compliers, that is, firms making investments in office and production

[21] In levels, the frontier share among office technology stood at 8.7 percent in 2021, while for production it was 4.2 percent, see Table A1 for current, retrospective, and prospective frontier technology shares in levels.

technologies due to the pandemic, together with the other categories of investing or non-investing firms.

First, consider office equipment (panel A). 70.1% of firms did not make any investment in frontier technologies at any point in time between 2016 and 2021 while 25.6% reported investments before the pandemic.[22] In contrast, only 7.5% of firms reported any investments during but not due to, and 10.1% reported making investments due to the pandemic. These 10.1% of firms are compliers according to our formal framework, while all other firms (89.9%) are never takers. Also, a large share of compliers conduct only secondary due-to investments, while only 3.7% of all firms report to have made a main investment due to the pandemic. Thus, while we observe a considerable share of firms investing due to the pandemic, only a minority reports major investments caused by the pandemic.

Next, consider production equipment (panel B). 87.8% of firms did not report any frontier investments during our period, while 11.6% invested before the pandemic, 3.9% during but not due to, and almost no firm reported investments due to the pandemic. That is, there are close to zero complier firms when it comes to production technologies.

Table 3 further displays the average change of frontier shares in each investment category as well as their percentage contributions to the overall change.[23] Three main findings stand out: First, the contributions of firms with main investments in office equipment due to the pandemic (15.0%) and during the pandemic (10.3%) are quite small compared to the contribution of firms with main investments before the pandemic (80.0%). Second, when taking into account secondary investments, investments by compliers account for 38.1% of the overall change in frontier office equipment (15.0% for main investments plus 23.1% for all firms with additional secondary due-to investments), although almost half of the overall change can still be attributed to main investors before the pandemic without any secondary investments. And third, the contribution of firms with due-to investments in production equipment to the overall change in the frontier technology share is negligible irrespective of whether focusing solely on main investments (1.5%) or adding secondary due-to investors (1.8%).[24]

In sum, the descriptive evidence speaks quite clearly against a pandemic push for production equipment, while the case may seem less clear for office equipment. On the one hand, there are 10.1% of compliers, that is, the set of firms investing in any frontier office equipment due to the pandemic is not negligible. On the other hand, a large share

[22]This is calculated as $22.3 + 0.8 + 0.5 + 2.0 = 25.6$ from the relevant numbers in Table 3.

[23]Note that the contribution of non-investors may be negative as those firms may still have invested in lower-level technologies, or because of depreciation of equipment.

[24]Table A3 displays a simplified version of Table 3, focusing only on main investments. Table A4 shows the simplified version but weighting by employment. The only notable difference to the firm-weighted results is that nearly 50 percent of employees worked in firms that invested in frontier technologies, while only 30 percent of firms invested.

of these firms conduct only secondary due-to investments, which may not represent a substantial increase in frontier technology use.

The descriptive evidence has two shortcomings. First, it does not allow us to disentangle the effects of different investments on frontier technology shares, since a firm may have invested, for instance, both before and due to the pandemic. Second, firms investing at different points in time or for different reasons differ by baseline characteristics, which may be related to differential technology adoption in the absence of the pandemic. In fact, frontier investors compared to non-investors are larger, more likely operating in knowledge-intensive sectors, have a more educated workforce and higher remote work potential, and exhibit higher frontier technology shares already in 2016. Differences among investors—say between due-to and before investors—are less pronounced but still exist. (See Table A2 for details on these comparisons.) We next use a regression framework to both address the selection concerns as well as to disentangle the effects on overall frontier technology adoption of main versus secondary and due-to versus before (and during-not-due-to) investments.

4.3 By how much did pandemic investments increase frontier technology shares?

Our aim in this section is to identify the marginal effect of due-to investments on the change in the frontier technology shares. As explained in Section 3.2, this corresponds to the ATT, the effect of the pandemic on firms that invest due to the pandemic. We regress the change in the frontier technology share of firm i over 2016–2021 on indicators characterizing the firm's investment activity. In particular, we estimate the model

$$\begin{aligned}&\Delta_{2016,2021}\text{ Frontier share}_i\\&\qquad=\lambda_1\text{Before}_i+\lambda_2\text{During, not due}_i+\lambda_3\text{Due to}_i+\beta X_i+\varepsilon_i,\end{aligned}\tag{1}$$

where Before_i, During, not due_i, and Due to_i are binary variables indicating investments in relation to the pandemic. When focusing on main investments, these indicators are mutually exclusive. However, when including secondary investments, this is no longer so, as discussed before and shown in Table 3. The advantage of the regression analysis is that we can estimate the effect of, say, investing due to the pandemic, holding constant whether the firm invested before or during but not due to the pandemic. In that case, λ_3 estimates the ATT for complier firms if there is no remaining selection bias.

To reduce selection bias, we control for firm characteristics X_i that may affect investment decisions. These include baseline technology shares in 2016, industry, firm size, AKM firm fixed effects (wage premium), region, share of remote work before the pandemic, and educational composition of the firm's workforce. To check for any remaining selection bias, we use frontier technology adoption plans, which panel firms reported in 2016, as an alternative dependent variable. We also use the panel firms to check whether our estimate is affected by any retrospective measurement error, by calculating baseline technology shares using 2016 survey responses.

Our analysis focuses on office equipment, since there exist hardly any production investments, main or secondary, that were due to the pandemic.[25] Panel A of Table 4 reports the results. Column (1) shows that all else equal, making an investment due to the pandemic appears to raise frontier technology shares by 5pp on average. Having made an investment before the pandemic appears to yield an increase that is more than double, namely 12.5pp, again all else equal. Still, column (1) indicates a statistically significant increase in the frontier technology share from due-to investments, suggesting that the ATT of the pandemic might be positive if any remaining selection bias was zero. The result is broadly similar for panel firms, irrespective of how changes in frontier shares are measured (columns (2) and (3)).

However, column (4) suggests that there remains positive selection bias. Conditional on the same set of controls, investments due to the pandemic are associated with more ambitious plans reported in 2016 already. Thus, it appears that compliers would have adopted frontier technology at a higher rate than never takers even in the absence of the pandemic, indicating that the estimated ATT is an upper bound on the true ATT.

Panel B of Table 4 confirms that due-to investments yield substantially lower increases in frontier shares because most of them are of secondary importance.[26] Indeed, column (1) reveals that frontier shares in office equipment increased by 14pp on average among firms with a main investment compared to non-investing firms. Additional secondary investments contribute very little. This also holds for the subsample of panel firms with either retrospective or contemporaneous measurement of frontier technology shares (columns (2) and (3)). Furthermore, we find that firms making secondary investments had substantially more ambitious plans in 2016 already (column (4)), again suggesting that complier firms are a positive selection of firms that are more inclined to conduct a secondary investment.

Thus, the rather small estimated ATT from panel A is largely accounted for by the fact that many of the due-to investments were secondary and thus less impactful. In fact, main investments due to the pandemic turn out to be comparable in raising the frontier technology share to main investments conducted before the pandemic or during but not

[25] We report results on production equipment in Table A5.

[26] The estimation equation underlying these results is

$$\Delta_{2016,2021} \text{ Frontier share}_i = \delta_1 \text{Main}_i + \delta_2 \text{Secondary}_i + \pi X_i + \eta_i.$$

Note that, by definition, secondary investments can only occur when the firm also made a main investment, so δ_2 gives the increase in the frontier share associated with a secondary investment over and above that implied by the main investment.

due to the pandemic, as seen in panel C of Table 4.[27] The estimated ATT may further be an upper bound of the pandemic's effect on compliers, since we found some evidence of positive selection bias for firms that invest due to the pandemic.

Given the recency of the Covid-19 pandemic, our results naturally speak to the short-run effect of the pandemic on frontier technology adoption. However, we also asked firms about their plans regarding frontier technology investments looking five years ahead. Here we briefly explore the associations between actual investments 2016–2021 and planned investments 2021–2026.

Column (5) in Panel A of Table 4 reveals a strong positive association between pre-pandemic investments and expected increases in frontier technology shares. In contrast, there is no evidence of an association between any pandemic-period investments (whether 'due to' or not) and future plans, when considering both main and secondary investments. Panel B again shows that this distinction matters: Having made any frontier investment is associated with greater planned frontier technology shares, as captured by the coefficient on the main investment dummy, but secondary investments are not associated with any additional expected increase. Results from the specification considering only main investments, but distinguishing investments by timing and motivation, are shown in column (5) of panel C. Investments 'due to' the pandemic do correlate positively with greater future adoption plans. However, we do not see this as sufficient evidence for a possible crisis push that has lasting impact, given that only 3.7 percent of firms made any main investment because of the pandemic.

4.4 Quantifying the overall effect of the pandemic

In the previous section, we reported a small and likely upward-biased estimate of the effect of due-to investments on the technology share of complier firms. To gauge the overall effect of the pandemic, we also need to take account of investments that were lost due to the pandemic. As we did not ask firms to report such canceled projects, we instead rely on counterfactual technology growth derived from extrapolating either pre-pandemic trends or plans.

To begin with, Column (1) of Table 5 provides the contribution of investments before and during the pandemic to the average change in frontier technology shares in office equipment as predicted by the estimated equation (1), shown in column (1) of panel A in Table 4. For the period before the pandemic, the regression predicts a 3.20pp increase of the frontier technology share, which stems from 25.6 percent of firms (see Table 3) making any main or secondary pre-pandemic investments with an average impact

[27]Results are largely unchanged when weighting the regressions by baseline employment, see Table A6. A notable difference is that workers in firms that made secondary investments, or in firms reporting 'due to' investments, did not see more ambitious investment plans at their firms, on average. Results are also robust to including potentially hidden 'during-not-due-to' investments, as shown in Table A7.

of 12.5pp (Table 4). The due-to investments during the pandemic imply an increase of overall technology shares of 0.51pp, which stems from 10.1 percent of firms making any due to investments with an average impact (ATT) of 5.0pp. Finally, the during-but-not-due-to investments lead to another minor increase of 0.13pp. The baseline change predicted by the regression (the average prediction for a firm not investing from 2016–2021) is -0.84, which is shown in the top row of column (1).

While not large in the first place, the 0.51pp increase implied by due-to investments is likely an upper bound for the overall effect of the pandemic on frontier technology shares. This is because it ignores the potentially left-out investments that did not occur (were canceled) due to the pandemic[28] as well as the likely positive selection of complier firms discussed in the previous section. These negative effects cannot directly, or separately, be measured but they may be inferred from extrapolating prior trends or plans.

First, consider the counterfactual based on the rate and impact of investments before the pandemic, shown in column (2) of Table 5. For the pre-pandemic period, this is by definition the same number as in column (1). For the pandemic period, the extrapolation yields a counterfactual increase of technology shares of 1.91pp (that is, around sixty percent of the pre-pandemic increase, reflecting relative period lengths).[29] This is in contrast to the much lower 0.64pp from during and due to investments in column (1) and, intuitively, simply the kink in the trend of investment rates that occurred after early 2020. Missing investments according to this extrapolation thus amount to 1.28pp in frontier technology shares.

Second, column (3) of Table 5 shows the counterfactual based on plans reported in 2016. On average, firms expected to raise their frontier technology shares by 5.64pp over 2011–2016. Apportioning this increase yields 3.53pp for the pre-pandemic period—very similar to the 3.20pp based on actual changes in column (1)—and for the pandemic period the calculation yields 2.11pp. This implies that canceled investments amounted to 1.48pp in frontier technology shares, similar to the loss calculated based on pre-pandemic trends.

We conclude that there is no evidence for an overall crisis push. Instead, the Covid-19 pandemic seems to have slowed down frontier technology adoption. In the absence of the pandemic, the use of frontier office technologies might have grown substantially more than the observed 3pp: For instance, nearly 50% more according to the counterfactual based on pre-pandemic trends. This is equivalent to about 1.4 years of investment activity

[28]Campello et al. (2010) found that more than half of firms canceled or postponed their planned investments during the 2008–09 financial crisis.

[29]We calculate the (relative) period lengths used in the counterfactuals as follows: Survey date minus February 2020, when the pandemic hit Europe, is the time during the pandemic and in the data, on average, 2.11 years. February 2020 minus the middle of the reference year (what the respondent considers the beginning of the period) is the time before the pandemic and, on average, 3.54 years. Most reference years are 2016—we consider respondents' views to refer to the middle of the year and subtract 2016.5—but there exist later reference years, too. See also Section 2.1.

during normal times.[30] The slow down, in terms of percentages and years of investment activity lost, is quite similar for production technology (compare Table A8).

5 Evidence on the crisis shift hypothesis

We now turn to the crisis shift hypothesis and examine the type of technologies firms invested in due to the pandemic. We use the responses to our open-ended question asking which specific frontier technologies firms invested in, combined with information on the timing of and reason for the investment.

5.1 Classifying frontier technologies by application

To classify frontier technology investments in different types of applications, we followed a supervised machine learning approach. We first asked ChatGPT to provide us with a description of each technology mentioned in the survey. Next, for both office and production equipment, we decided on a list of categories to group the applications. In the case of office equipment, these include 'communication and collaboration tools', 'cloud computing', and 'basic IT infrastructure', among others. We then created a training data set where we manually categorized a subset of technologies. Using this data set, we trained a Neural Network Classifier (NNC) that categorized the remaining technologies based on the descriptions provided by ChatGPT.[31] We thus were able to categorize a total of 2,526 office technologies and 457 production technologies. For a more detailed description, together with an evaluation of the prediction quality, see Appendix B.4.

5.2 Shifts between areas of frontier technology investments

Our data are now at the level of individual technology investments, so that there can be multiple observations per firm. We explore shifts in the composition of frontier investments by comparing the distribution of applications across the categories before, during but not due to, and due to the pandemic.

Figure 2 shows the results. Consider first investments made before the pandemic, indicated by the gray bars. About half of these investments were in 'basic IT infrastructure' or 'e-commerce and customer interaction'. By contrast, 'IT infrastructure for remote

[30] We estimate this based on the yearly investment rate prior to the pandemic of 3.2pp over 3.54 years, amounting to 0.904pp per year. A decline of 1.28pp due to the pandemic then corresponds to 1.28pp divided by 0.904pp per year, or 1.42 years of investment activity during pre-Covid times.

[31] Descriptions were pre-processed using tokenization, removing stop words, and lemmatization before transforming them into an input vector. Parameters of the NNC were chosen based on hyperparameter tuning using GridSearch. Using the descriptions, rather than just the technologies mentioned by the respondents, helped distinguish falsely similar cases like Microsoft Office and Microsoft Cloud.

work' and 'communication and collaboration tools' together accounted for just above 10 percent of pre-pandemic investments.

The picture changes markedly when considering investments due to the pandemic, shown in dark blue shades. More than half of investments made because of the pandemic belong to 'IT infrastructure for remote work' or 'communication and collaboration tools'.[32] Most of these were secondary investments, as indicated by the slightly lighter shading. Perhaps surprisingly, 'cloud computing infrastructure' is represented to a similar extent among pre-pandemic and due-to investments. Technologies facilitating management, product design, and planning are nearly absent among the due-to investments, but account for about 12 percent of both pre-pandemic investments and investments made during the pandemic but not because of it.

In sum, we observe clear shifts in the nature of frontier technology investments due to the pandemic. Consistent with the absence of a pandemic push, many of these pandemic-induced investments were secondary investments.[33]

5.3 Technology shifts and firm-level employment

Figure 2 showed that 'IT infrastructure for remote work' as well as 'communication and collaborations tools' represent disproportionately high shares of firms' pandemic investments. This suggests that these investments were made in order to allow work processes to continue despite social distancing requirements, lock-downs, and the like. We now explore whether such pandemic investments are indeed associated with employment outcomes at the firm level, thereby also shedding light on the question whether technological adaptation can help mitigate the impact of adverse shocks on a firm's workforce.

Evaluating employment outcomes during the pandemic in Germany is challenging because of the prevalence of state-financed short-time work schemes (STW).[34] During the pandemic, these were used extensively by firms, such that the size of a firm's work force may not have changed much despite declining hours of work. We therefore not only study overall employment, but also the firm's share of employment not liable to social insurance payments or 'non-regular' employment—which are mostly marginal employees and not eligible for short-time work—and the STW share itself.

[32]Communication and collaboration tools were also quite common among during-not-due-to investments.

[33]Strengthening the plausibility of a causal interpretation further, these shifts are not merely due to differences between complier and non-complier firms: They are present even within complier firms, that is, limiting the sample to those firms that reported any due-to investment. See Figure A1. For completeness, Figure A2 repeats the analysis underlying Figure 2 for production equipment.

[34]For a details on STW coverage and replacement rates during the pandemic, see Appendix B.3.

We estimate at the firm level the model

$$\begin{aligned}\Delta_{2019,2021} & \text{ Employment outcome}_i \\ & = \kappa_1 \text{Before}_i + \kappa_2 \text{During, not due}_i + \kappa_3 \text{Due to}_i + \gamma X_i + u_i,\end{aligned} \tag{2}$$

where the employment outcomes are changes between 2019 (that is, before the pandemic) and 2021, in: the share of employees working from home (WfH) as elicited by our survey; overall log employment; the share of non-regular employment in total employment; or the share of short-time work.[35] The coefficient on having invested due to the pandemic, κ_3, captures the effect of being a complier on the respective employment outcome—the ATT for complier firms—if there is no remaining selection bias. We try to minimize potential selection bias not only by controlling for the same set of firm characteristics used above, X_i, but also supplement the control set with measures of the firm's exposure to the Covid shock.[36]

Table 6 reports results from estimating equation (2). Column (1) shows a strong positive association between investing due to the pandemic and the rise in the WfH share. The estimate of 21pp is large in magnitude given an average increase of 15pp. In contrast, investments before the pandemic are not associated with changes in the WfH share, and neither are investments during the pandemic that are not due to it. The result is also robust to controlling for the pandemic exposure variables (column (2)). This evidence is consistent with the notion that complier firms specifically invest *in order to* facilitate remote work, in accordance with the crisis shift hypothesis. Of course, we cannot completely rule out selection bias.

Columns (3)–(6) of Table 6 show imprecisely estimated coefficients when overall employment growth and growth in non-regular employment are the left-hand side variables. The point estimates for due-to investments are positive and of non-negligible magnitude, at least not rejecting the notion that these investments mitigated employment losses. There is somewhat stronger evidence that due-to investments counterbalanced

[35]The survey asks about the share of the firm's employment working from home at the time of the interview and before the pandemic. The change in short-time work, marginal employment, and total employment between 2019 and 2021 is based on administrative data.

[36]These measures include the log number of weeks of forced firm closure, a dummy for severe supply chain problems, a dummy for decline in product demand, a dummy for application for Covid-19 support, a dummy for severe uncertainty, a dummy for firm-specific decline in revenues during the pandemic, log remote work potential, log industry decline in revenue during the pandemic, and Covid-19 hospitalization rate in 2020. Further, including the respective lagged outcome variable ($\Delta_{2016,2019}$ Employment outcome$_i$) in the set of controls in columns (3)–(6) does not change the results substantively.

the economy-wide increase in STW of on average 11pp: This increase is lower by about 5–7pp among firms that invested due to the pandemic (columns (7)-(8)).[37,38]

Finally, we have also investigated the associations between due-to investments by application and employment outcomes. Indeed, 'IT infrastructure for remote work' as well as 'communication and collaboration tools'—both of which became much more common due to the pandemic—are strongly positive related to the WfH share (see Table A9). These associations weaken somewhat when including investments that were not made due to the pandemic.[39] Again, despite remaining concerns about selection bias, these results are at the minimum suggestive of a crisis shift.

6 Conclusion

Recent research in macroeconomics has suggested an important relationship between business cycles and economic growth.[40] In this paper, we obtained new microeconomic evidence on a particular channel for this relationship. We find that firm-level technology adoption markedly slowed down during the Covid-19 crisis, resulting in a loss of 1.4 years' worth of investment activity during normal times. Although the pandemic induced a shift toward adopting remote work technologies that helped firms stabilize employment, these rather small scale investments were not sufficient to compensate for the loss of larger investments that firms would have conducted in absence of this crisis. We find no evidence for a positive medium-run effect either, as pandemic investments show no correlation with future investment plans, unlike investments before the pandemic.

Serious economic crises only occur at low frequency and usually for a variety of reasons. Therefore, longstanding research on this topic has often treated individual crises as case studies, untangling critical commonalities and differences between them (see, for example, the seminal contributions by Romer, 1990a; Bloom, 2009; Reinhart and Rogoff, 2009). Consistent with this approach, we have focused in our paper on the specific pandemic crisis

[37]In columns (7)-(8), there is also a positive and statistically significant association of during-not-due-to investments and the short-time work share. This may be related to the opportunity cost channel discussed in Section 3. Because of low demand and the option to have their workers paid through the government STW scheme, some firms find it optimal to shut down production while installing new technologies during the pandemic. Overall, as we have seen, such firms are too few and their effects on technology shares too small, for an economy-wide crisis push.

[38]Oikonomou et al. (2023) find that US regions with greater pre-pandemic IT adoption rates experienced less severe unemployment during the pandemic. Unlike our dataset, theirs does not contain information on investment responses during or due to the pandemic.

[39]This last result is not shown in the table for brevity. 'Cloud computing infrastructure' and 'data analytics and visualization equipment' also have strong associations with WfH but especially the latter are much less common in the pandemic, see Figure 2.

[40]For example, Barlevy (2004) argues that more volatile investment will lead to lower compound growth rates, while Terry (2023) focuses on the deleterious effects of short-termism, which should be more prevalent in crises. Jordà et al. (2020) find strong hysteresis in the capital stock and total factor productivity. Cerra et al. (2023) review this growing literature and summarize recent evidence.

while also carefully highlighting its more general business cycle features. Our argument has been that, overall, the pandemic created relatively strong incentives for experimenting with new technologies compared to other crises. In light of this argument, a broader interpretation of our empirical results suggests that crises may also generally slow down the diffusion of frontier technologies, and thereby long-run economic growth.

In the specific case of Germany, recent trends in economic growth and productivity have been particularly disappointing. During 2019–2023, hourly labor productivity grew by only 0.47 percent annually compared to, for example, 1.77 percent in the United States (OECD, 2024). Given our findings, part of this under-performance could be due to the fact that Germany has been more exposed to a series of increasingly frequent shocks including Covid-19 but also more recently the Ukraine crisis. In particular, the energy price and uncertainty shocks that occurred immediately after the pandemic may have contributed to a sustained decline of frontier technology investments in Germany. This highlights the continued importance of growth-supporting policies (Draghi, 2024). Our results also raise the question whether innovation policy should be counter-cyclical, which is an important area for future research.

References

ACEMOGLU, D. (2002): "Directed technical change," *The Review of Economic Studies*, 69, 781–809.

ACEMOGLU, D., P. AGHION, L. BURSZTYN, AND D. HEMOUS (2012): "The environment and directed technical change," *American Economic Review*, 102, 131–166.

ACEMOGLU, D., G. W. ANDERSON, D. N. BEEDE, C. BUFFINGTON, E. E. CHILDRESS, E. DINLERSOZ, L. S. FOSTER, N. GOLDSCHLAG, J. C. HALTIWANGER, Z. KROFF, P. RESTREPO, AND N. ZOLAS (2022): "Automation and the Workforce: A Firm-level View from the 2019 Annual Business Survey," NBER Working Paper No. 30659, National Bureau of Economic Research.

ACEMOGLU, D., C. LELARGE, AND P. RESTREPO (2020): "Competing with Robots: Firm-Level Evidence from France," *AEA Papers and Proceedings*, 110, 383–88.

ACEMOGLU, D. AND P. RESTREPO (2022): "Demographics and automation," *The Review of Economic Studies*, 89, 1–44.

AGHION, P., G.-M. ANGELETOS, A. BANERJEE, AND K. MANOVA (2010): "Volatility and growth: Credit constraints and the composition of investment," *Journal of Monetary Economics*, 57, 246–265.

AGHION, P., P. ASKENAZY, N. BERMAN, G. CETTE, AND L. EYMARD (2012): "Credit constraints and the cyclicality of R&D investment: Evidence from France," *Journal of the European Economic Association*, 10, 1001–1024.

AGHION, P. AND P. HOWITT (1992): "A Model of Growth Through Creative Destruction," *Econometrica*, 60, 323–351.

AGHION, P. AND G. SAINT-PAUL (1998): "Virtues of bad times interaction between productivity growth and economic fluctuations," *Macroeconomic Dynamics*, 2, 322–344.

ALTIG, D., S. BAKER, J. M. BARRERO, N. BLOOM, P. BUNN, S. CHEN, S. J. DAVIS, J. LEATHER, B. MEYER, E. MIHAYLOV, ET AL. (2020): "Economic uncertainty before and during the COVID-19 pandemic," *Journal of Public Economics*, 191, 104274.

ARNTZ, M., S. GENZ, T. GREGORY, F. LEHMER, AND U. ZIERAHN-WEILAGE (2024): "De-routinization in the Fourth Industrial Revolution–Firm-Level Evidence," *ZEW-Centre for European Economic Research Discussion Paper*.

Avalos, E., X. Cirera, M. Cruz, L. Iacovone, D. Medvedev, G. Nayyar, and S. R. Ortega (2023): "Firms' Digitalization during the COVID-19 Pandemic," Policy Research Working Paper 10284, World Bank Group.

Barlevy, G. (2004): "The Cost of Business Cycles Under Endogenous Growth," *American Economic Review*, 94, 964–990.

——— (2007): "On the cyclicality of research and development," *American Economic Review*, 97, 1131–1164.

Barrero, J. M., N. Bloom, and S. J. Davis (2021): "Why working from home will stick," Tech. rep., National Bureau of Economic Research.

——— (2023): "The Evolution of Work from Home," *Journal of Economic Perspectives*, 37, 23–50.

Barth, E., A. Bryson, and H. Dale-Olsen (2022): "Creative Disruption: Technology Innovation, Labour Demand and the Pandemic," .

Bellmann, L., B. Lochner, S. Seth, and S. Wolter (2020): "AKM effects for German labour market data," FDZ-Methodenreport, 01/2020 en, Institute for Employment Research.

Benhabib, J., J. Perla, and C. Tonetti (2014): "Catch-up and fall-back through innovation and imitation," *Journal of Economic Growth*, 19, 1–35.

Bessen, J., M. Goos, A. Salomons, and W. van den Berge (2020): "Firm-level automation: Evidence from the Netherlands," *AEA Papers and Proceedings*, 110, 389–393.

Bick, A., A. Blandin, and K. Mertens (2023): "Work from home before and after the COVID-19 outbreak," *American Economic Journal: Macroeconomics*, 15, 1–39.

Bloom, N. (2007): "Uncertainty and the Dynamics of R&D," *American Economic Review*, 97, 250–255.

——— (2009): "The impact of uncertainty shocks," *Econometrica*, 77, 623–685.

Bloom, N., S. Bond, and J. Van Reenen (2007): "Uncertainty and Investment Dynamics," *The Review of Economic Studies*, 74, 391–415.

Bloom, N., S. J. Davis, and Y. Zhestkova (2021): "Covid-19 shifted patent applications toward technologies that support working from home," in *AEA Papers and Proceedings*, American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203, vol. 111, 263–266.

BLOOM, N., J. LIANG, J. ROBERTS, AND Z. J. YING (2015): "Does Working from Home Work? Evidence from a Chinese Experiment," *The Quarterly Journal of Economics*, 130, 165–218.

BLOOM, N. AND J. VAN REENEN (2007): "Measuring and explaining management practices across firms and countries," *The Quarterly Journal of Economics*, 122, 1351–1408.

BÖHM, M. J. AND P. QENDRAI (2023): "System Relevance and Firm Performance Due to COVID-19," *German Economic Review*, 24, 349–410.

BRUHNS, F., B. MATTHES, AND M. STOPS (2024): "HOP – an occupational indicator for the potential of Working From Home," *mimeo*.

BRYAN, K. A. AND H. L. WILLIAMS (2021): "Chapter 13 - Innovation: market failures and public policies," in *Handbook of Industrial Organization, Volume 5*, ed. by K. Ho, A. Hortaçsu, and A. Lizzeri, Elsevier, vol. 5 of *Handbook of Industrial Organization*, 281–388.

CAMPELLO, M., J. R. GRAHAM, AND C. R. HARVEY (2010): "The real effects of financial constraints: Evidence from a financial crisis," *Journal of Financial Economics*, 97, 470–487.

CARD, D., J. HEINING, AND P. KLINE (2013): "Workplace Heterogeneity and the Rise of West German Wage Inequality," *The Quarterly Journal of Economics*, 128, 967–1015.

CERRA, V., A. FATÁS, AND S. C. SAXENA (2023): "Hysteresis and business cycles," *Journal of Economic Literature*, 61, 181–225.

DRAGHI, M. (2024): "The future of European competitiveness," report, European Commission.

DRAHOKOUPIL, J. AND T. MÜLLER (2021): "Job retention schemes in Europe: A lifeline during the Covid-19 pandemic," *ETUI Research Paper-Working Paper*.

DUSTMANN, C., J. LUDSTECK, AND U. SCHÖNBERG (2009): "Revisiting the German Wage Structure," *The Quarterly Journal of Economics*, 124, 843–881.

FRANCOIS, P. AND H. LLOYD-ELLIS (2003): "Animal spirits through creative destruction," *American Economic Review*, 93, 530–550.

GAGGL, P. AND G. C. WRIGHT (2017): "A short-run view of what computers do: Evidence from a UK tax incentive," *AEJ: Applied Economics*, 9, 262–94.

GARTNER, H., C. HUTTER, AND E. WEBER (2022): "Wie der Arbeitsmarkt zwei sehr unterschiedliche Krisen bewältigt," *IAB-Kurzbericht*, 27, 2021.

Gathmann, C., C. Kagerl, L. Pohlan, and D. Roth (2024): "The pandemic push: Digital technologies and workforce adjustments," *Labour Economics*, 102541.

Genz, S., T. Gregory, M. Janser, F. Lehmer, and B. Matthes (2021): "How do workers adjust when firms adopt new technologies?" *ZEW-Centre for European Economic Research Discussion Paper.*

German Ministry of Economic Affairs (2022): "Informationen zu Corona-Hilfen des Bundes," `https://www.bmwk.de/Redaktion/DE/Coronavirus/informationen-zu-corona-hilfen-des-bundes.html`, retrieved November 5, 2022.

German Ministry of Finance (2020): "Weg für Gewährung der Corona-Bundes-Soforthilfen ist frei—Umsetzung durch die Länder steht," `https://www.bundesfinanzministerium.de/Content/DE/Pressemitteilungen/Finanzpolitik/2020/03/2020-03-29-PM-Verwaltungsvereinbarung-Soforthilfe.html`, retrieved November 5, 2022.

Gopinath, G., Ş. Kalemli-Özcan, L. Karabarbounis, and C. Villegas-Sanchez (2017): "Capital allocation and productivity in South Europe," *The Quarterly Journal of Economics*, 132, 1915–1967.

Griliches, Z. (1957): "Hybrid Corn: An Exploration in the Economics of Technological Change," *Econometrica*, 25, 501–522.

Hershbein, B. and L. B. Kahn (2018): "Do recessions accelerate routine-biased technological change? Evidence from vacancy postings," *American Economic Review*, 108, 1737–1772.

Jaimovich, N. and H. E. Siu (2020): "Job polarization and jobless recoveries," *Review of Economics and Statistics*, 102, 129–147.

Jordà, Ò., S. R. Singh, and A. M. Taylor (2020): "The Long-Run Effects of Monetary Policy," NBER Working Papers 26666, National Bureau of Economic Research, Inc.

Koch, M., I. Manuylov, and M. Smolka (2021): "Robots and Firms," *The Economic Journal*, 131, 2553–2584.

LaBerge, L., C. O'Toole, J. Schneider, and K. Smaje (2020): "How COVID-19 has pushed companies over the technology tipping point—and transformed business forever," Technical report, McKinsey & Company.

McElheran, K., J. F. Li, E. Brynjolfsson, Z. Kroff, E. Dinlersoz, L. S. Foster, and N. Zolas (2022): "AI Adoption in America: Who, What, and Where," NBER Working Paper No. 31788, National Bureau of Economic Research.

Morikawa, M. (2021): "Uncertainty of firms' economic outlook during the COVID-19 crisis," *Covid Economics*, 81.

Newell, R. G., A. B. Jaffe, and R. N. Stavins (1999): "The Induced Innovation Hypothesis and Energy-Saving Technological Change," *The Quarterly Journal of Economics*, 114, 941–975.

OECD (2024): "Productivity growth rates," Organisation for Economic Co-operation and Development, `https://data-explorer.oecd.org/`, retrieved July 15, 2024.

Oikonomou, M., N. Pierri, and Y. Timmer (2023): "IT shields: Technology adoption and economic resilience during the COVID-19 pandemic," *Labour Economics*, 81, 102330.

Reinhart, C. M. and K. S. Rogoff (2009): *This Time Is Different: Eight Centuries of Financial Folly*, Princeton University Press.

Romer, C. D. (1990a): "The Great Crash and the Onset of the Great Depression*," *The Quarterly Journal of Economics*, 105, 597–624.

Romer, P. M. (1990b): "Endogenous Technological Change," *Journal of Political Economy*, 98, S71–S102.

Roth, C. and J. Wohlfart (2020): "How Do Expectations about the Macroeconomy Affect Personal Expectations and Behavior?" *The Review of Economics and Statistics*, 102, 731–748.

Stantcheva, S. (2023): "How to run surveys: A guide to creating your own identifying variation and revealing the invisible," *Annual Review of Economics*, 15, 205–234.

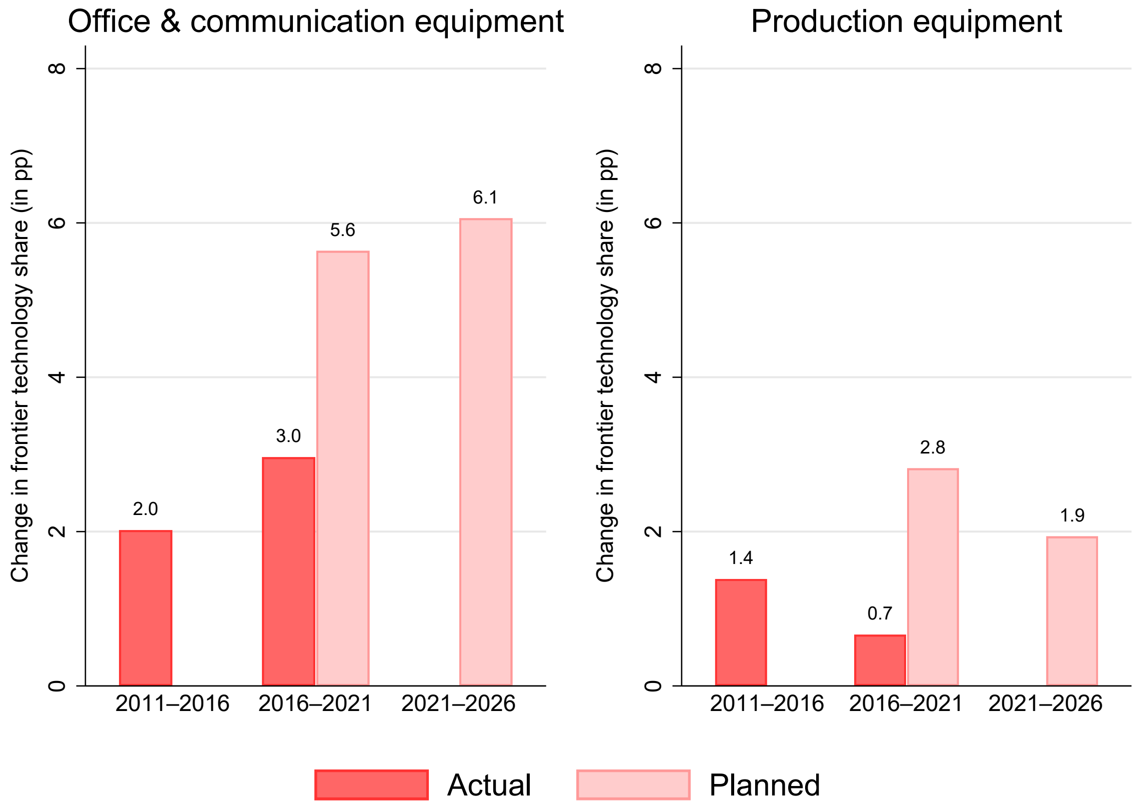
Terry, S. J. (2023): "The Macro Impact of Short-Termism," *Econometrica*, 91, 1881–1912.

Valero, A., C. Riom, and J. Oliveira-Cunha (2021): "The business response to Covid-19 one year on: findings from the second wave of the CEP-CBI survey on technology adoption," CEP Covid-19 Analysis 024, Centre for Economic Performance (CEP).

Wiswall, M. and B. Zafar (2021): "Human capital investments and expectations about career and family," *Journal of Political Economy*, 129, 1361–1424.

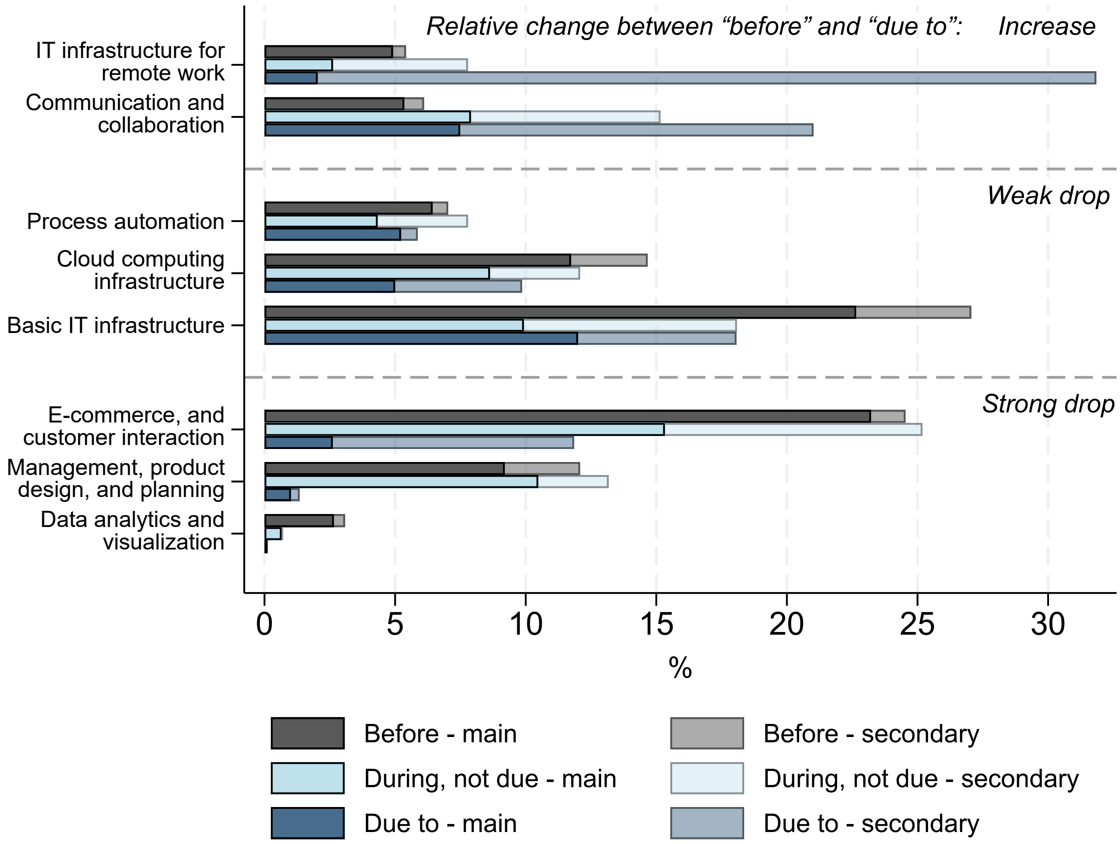
Zolas, N., Z. Kroff, E. Brynjolfsson, K. McElheran, D. N. Beede, C. Buffington, N. Goldschlag, L. Foster, and E. Dinlersoz (2020): "Advanced technologies adoption and use by US Firms: Evidence from the annual business survey," NBER Working Paper No. 28290, National Bureau of Economic Research.

Figure 1: Changes in frontier technology shares



Notes: The figure displays changes in the share of work equipment that respondents classified as frontier technology (see Table 1), averaged across all firms in each survey wave using sampling weights. The actual change is the difference between the current share and the share five years prior, the latter being based on respondents' recollections. The planned change is the difference between the respondents' expectation five years ahead and the current share.

Figure 2: Investments in office & communication equipment by application



Notes: For each investment category of ‘before’, ‘during not due to’, and ‘due to’ the pandemic, the bars show the percentage share of different kinds of applications (as indicated by the vertical axis labels) within that category. Bars add up to 100 for each category of ‘before’, ‘during not due to’, and ‘due to’. Percentage shares are based on 2,526 unique investments and are weighted by sampling weights. Applications are ranked in decreasing order according to the relative change between ‘before’ and ‘due to’.

Table 1: Characterizing firms' work equipment by technology levels

Technology levels (industrial revolutions)	Office & communication equipment	Production equipment
Frontier technology (4th Industrial Revolution, 2nd Digital Revolution) Technology performs work process autonomously	**IT-integrated** Cloud computing Chat bot Automated marketing	**Self-controlled** Manufacturing execution system Smart robot Predictive maintenance
Digital technology (3rd Industrial Revolution, 1st Digital Revolution) Humans indirectly involved in work process	**IT-supported** Personal computer Computer-aided design Electronic checkout	**Indirectly controlled** CNC machine Industrial robot Process engineering
Manual technology (1st/2nd Ind. Revolutions, before Digital Revolution) Humans conduct work process	**Not IT-supported** Telephone Fax Copy machine	**Manually controlled** Drilling machine Motor vehicle X-ray machine

Notes: The table describes the technology levels, along with examples, that we introduced to respondents during the interview. We asked respondents to estimate how their work equipment is divided across these levels (in percent).

Table 2: Descriptive statistics

	Cross section 2021			Panel		
	All	*No missings*		*All*	*No missings*	
	Mean	Mean	SD	Mean	Mean	SD
	(1)	(2)	(3)	(4)	(5)	(6)
Firm size						
0-9 employees	78%	75%		76%	75%	
10-49 employees	18%	20%		20%	21%	
50-199 employees	4%	4%		3%	3%	
200+ employees	1%	1%		1%	1%	
Sector						
Manuf. knowledge intensive	1%	2%		2%	1%	
Manuf. non-knowledge intensive	20%	21%		20%	20%	
Services knowledge intensive	22%	21%		21%	16%	
Services non-knowledge intensive	54%	54%		55%	61%	
Information & com. technology	3%	2%		2%	2%	
East Germany	20%	20%		19%	18%	
Covid affectedness						
Severe supply chain problems		55%		56%	59%	
Decline in product demand		27%		19%	21%	
Applied for covid-19 support		35%		34%	36%	
Severe uncertainty		33%		34%	37%	
Decline in revenues		22%		28%	32%	
Covid-19 hosp. rate 2020		0.05	0.02	0.05	0.05	0.02
Δ log industry revenue (during)		-0.01	0.17	0.01	0.01	0.10
Δ log industry revenue (pre)		0.13	0.11	0.13	0.13	0.11
#weeks forced closure		5	12	4	4	10
Log #weeks forced closure		0.70	1.26	0.65	0.69	1.21
Technology share (before Covid)						
Manual technology (1.0/2.0)		44%	27%	49%	50%	29%
Digital technology (3.0)		52%	27%	47%	47%	29%
Frontier technology (4.0)		4%	11%	4%	3%	9%
Remote work						
Initial share of remote work		6%	17%	6%	5%	13%
Remote work potential		0.41	0.20	0.38	0.36	0.20
Log remote work potential		-1.04	0.56	-1.12	-1.16	0.56
Employees' education						
No vocational training		5%	14%	6%	6%	15%
Vocational training		73%	33%	76%	76%	30%
University degree		19%	30%	13%	13%	24%
Employees' job skill level						
Helpers/assistants		13%	25%	14%	14%	24%
Skilled employees		64%	35%	68%	68%	32%
Specialists		11%	22%	11%	11%	20%
Experts		12%	24%	6%	6%	13%
AKM firm fixed effect		-0.08	0.20	-0.10	-0.10	0.25
Observations	2,985	2,268		465	388	

Notes: All statistics (other than number of observations) are calculated using sampling weights. Technology shares refer to office & communication equipment. Revenue changes during Covid are calculated at the 2-digit industry level as $\log(R_{i,t=2020}/R_{i,t=2019})$, where $R_{i,t}$ is the sum of revenues in industry i at time t. Revenue changes pre-Covid are averaged across years and calculated as $\frac{1}{3}\sum_{t=2017}^{2019}\log(R_{i,t}/R_{i,t-1})$.

Table 3: Characteristics of frontier technology investments

Main investment	Secondary investments	% share of firms (1)	Δ frontier technology share (2)	% of overall change (3)	Observations (4)
A: Frontier investments in office and communication equipment					
None		70.1	−0.2	−5.2	1,150
Before	None	13.6	11.0	49.6	407
	During, not due to	3.6	7.9	9.6	182
	Due to	5.0	12.3	20.7	200
	Subtotal	22.3	10.8	80.0	789
During, not due to	None	1.7	9.5	5.5	53
	Before	0.8	8.5	2.4	62
	Due to	0.9	2.8	0.8	44
	Before & due to	0.5	9.7	1.6	65
	Subtotal	3.9	7.8	10.3	224
Due to	None	1.7	10.4	5.9	39
	Before	2.0	13.3	9.1	66
	Subtotal	3.7	12.0	15.0	105
Total		100.0	3.0	100.0	2,268
B: Frontier investments in production equipment					
None		87.8	0.0	−0.1	1,060
Before	None	8.2	4.9	66.6	182
	During, not due to	2.9	3.6	17.5	52
	Due to	0.0	2.1	0.1	3
	Subtotal	11.1	4.6	84.2	237
During, not due to	None	0.5	8.1	6.3	20
	Before	0.5	8.8	7.9	27
	Due to	0.0	20.0	0.2	1
	Before & due to	0.0	0.0	0.0	1
	Subtotal	1.0	8.5	14.3	49
Due to	None	0.0	19.8	1.5	5
	Subtotal	0.0	19.8	1.5	5
Total		100.0	0.6	100.0	1,351

Notes: 'Δ frontier technology share' is the average change in the share of frontier technologies within each investment category. '% of overall change' is the percentage share this category amounts to in the overall change in the share of frontier technologies, that is, the product of 'Share of firms' and 'Δ frontier technology share' divided by the total (average) change observed. All statistics other than number of observations are calculated using sampling weights.

Table 4: Changes in frontier technology shares by investment characteristics—office & communication equipment

	Change in frontier technology share				
	2016–21				2021–26
	Retrospective		Actual	Planned	Planned
	(1)	(2)	(3)	(4)	(5)
A: Before, during, due to (main and secondary investments)					
Before	12.5***	15.0***	12.6***	2.96	8.81***
	(1.55)	(2.01)	(3.13)	(2.08)	(2.14)
During, not due to	1.70	3.41	2.40	-3.57	-0.54
	(1.47)	(2.50)	(5.35)	(3.85)	(1.78)
Due to	5.00***	7.36***	3.84	7.32***	-0.027
	(1.81)	(2.13)	(3.01)	(2.58)	(2.50)
R-squared (adjusted)	0.41	0.81	0.65	0.40	0.16
B: Main vs. secondary					
Main	14.0***	16.5***	13.4***	1.44	7.69***
	(1.63)	(2.04)	(3.47)	(2.24)	(2.18)
Secondary	0.72	4.32	1.50	8.14**	0.26
	(1.94)	(2.62)	(4.10)	(3.28)	(2.34)
R-squared (adjusted)	0.42	0.82	0.66	0.39	0.15
C: Before, during, due to (only main investments)					
Before	14.8***	18.8***	14.7***	5.79***	9.17***
	(1.60)	(1.82)	(2.85)	(2.15)	(2.17)
During, not due	10.1***	16.2***	8.44	2.74	0.20
	(1.33)	(2.09)	(6.90)	(5.92)	(2.00)
Due to	15.7***	16.8***	13.1**	0.63	8.25**
	(1.78)	(2.55)	(5.26)	(2.75)	(3.40)
R-squared (adjusted)	0.43	0.82	0.66	0.38	0.16
Observations	2,268	388	388	388	2,268
Mean of dependent variable	3.0	2.4	-2.4	4.9	5.7
Panel firms only		✓	✓	✓	

Notes: The table reports results from regressing changes in shares of frontier technology on the right-hand-side variables listed in the left-most column—indicating the presence of investments with the stated characteristics—as well as controls. Non-investors are the excluded category in each case. Controls include baseline technology shares, industry dummies (10 categories), firm size dummies (4 categories), federal state dummies (16 categories) interacted with urban status, dummies for the month of interview (10 categories), remote work use before the pandemic, initial employee education (3 categories), initial employee job requirement levels (4 categories), and AKM firm fixed effects. Regressions are weighted using sampling weights (cross-sectional or longitudinal as appropriate). Robust standard errors in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

Table 5: Actual versus counterfactual change in frontier technology share—office & communication equipment

	Actual change	Counterfactual change based on	
	Regression-based decomposition	Pre-pandemic investments	Planned investments
	(1)	(2)	(3)
Baseline (no investment)	−0.84	−0.84	–
Before	3.20	3.20	*3.53*
During not due	0.13	*1.91*	*2.11*
Due to	0.51		
Full period	3.00	*4.28*	5.64

Notes: Column (1) displays a decomposition based on the estimated equation (1),

$$\overline{\Delta_{2016,2021} \text{ Frontier technology share}_i} = \widehat{\lambda_1} \times \overline{\text{Before}_i} + \widehat{\lambda_2} \times \overline{\text{During, not due}_i} + \widehat{\lambda_3} \times \overline{\text{Due to}_i} + \widehat{\beta} \times \overline{X_i},$$

where bars indicate sample means and hats represent OLS estimates, as reported in Tables 3 and 4. That is, each row reports a product of an estimated coefficient and its corresponding sample mean, with the first row referring to the prediction based on the controls X_i. Column (2) extrapolates the estimated change from column (1) for before investments to the period during the pandemic. Column (3) distributes the planned investments for the whole period as reported in Figure 1 to the period before and during the pandemic but without having an explicit prediction in the first line of what happens to non-investors. All extrapolations (in italics) attribute 63% (37%) of the overall change to the before (during) period given that the before period was on average approximately 3.54 years, while the average period during the pandemic was 2.11 years long.

Table 6: Investment decisions and employment

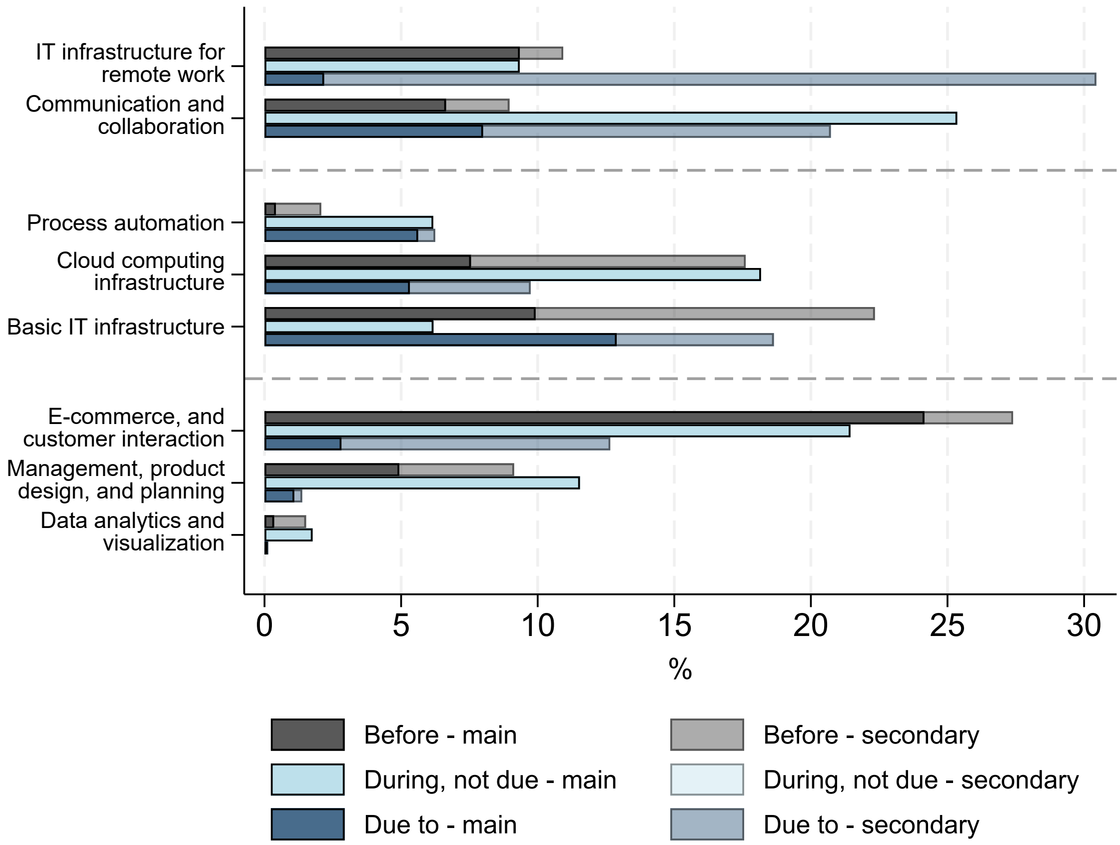
	Δ employees working from home in %		Δ log employment × 100		Δ share of employment not liable to social security in %		Employees in short-time work in 2021 in %	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Before	-2.21	-3.87	-2.36	-7.09	2.13	2.11	-1.37	0.23
	(2.84)	(2.86)	(4.69)	(5.60)	(1.85)	(1.98)	(2.57)	(2.35)
During, not due to	2.07	2.83	-1.77	0.89	0.14	-0.28	17.1***	11.1***
	(3.39)	(3.05)	(6.75)	(6.77)	(2.15)	(2.26)	(5.75)	(4.13)
Due to	21.4***	20.5***	6.04	4.39	1.22	2.12	-6.78*	-4.91*
	(4.60)	(4.44)	(5.93)	(5.77)	(1.86)	(1.83)	(3.90)	(2.98)
Observations	2,214	2,214	2,244	2,244	2,244	2,244	2,145	2,145
R-squared	0.32	0.38	0.15	0.20	0.11	0.14	0.24	0.39
Mean of dependent variable	15.0	15.0	-4.7	-4.7	-2.4	-2.4	10.9	10.9
Covid controls		✓		✓		✓		✓

Notes: The table reports results from regressing changes in employment indicators 2019–2021 on dummies for having invested in frontier technology before, during (though not due to), or due to the pandemic as well as controls. Controls include baseline technology shares, industry dummies (10 categories), firm size dummies (4 categories), federal state dummies (16 categories) interacted with urban status, dummies for the month of interview (10 categories), remote work use before the pandemic, initial employee education (3 categories), initial employee job requirement levels (4 categories), and AKM firm fixed effects. 'Covid controls' include the variables shown in Table A10. Regressions are weighted using sampling weights. Robust standard errors in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

Appendices for online publication

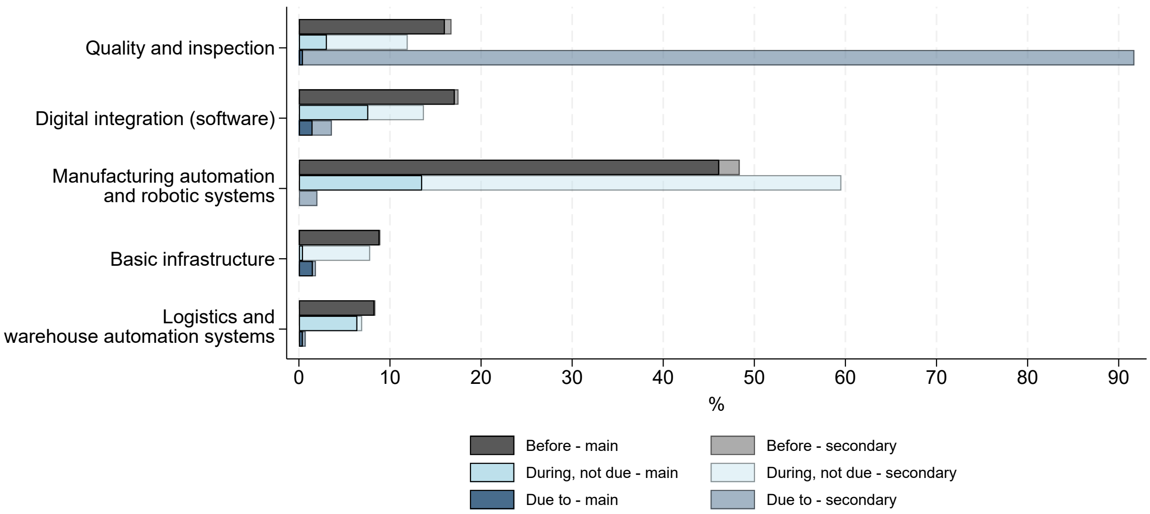
A Appendix figures and tables

Figure A1: Investments in office & communication equipment by application—compliers only



Notes: The sample is restricted to firms that made an investment due to the pandemic. For each investment category of 'before', 'during not due to', and 'due to' the pandemic, the bars show the percentage share of different kinds of applications (as indicated by the vertical axis labels) within that category. Bars add up to 100 for each category of 'before', 'during not due to', and 'due to'. Percentage shares are based on 1,154 unique investments and are weighted by sampling weights.

Figure A2: Investments in production equipment by application



Notes: For each investment category of 'before', 'during not due to', and 'due to' the pandemic, the bars show the percentage share of different kinds of applications (as indicated by the vertical axis labels) within that category. Bars add up to 100 for each category of 'before', 'during not due to', and 'due to'. Percentage shares are based on 457 unique investments and are weighted by sampling weights. Applications are ranked in decreasing order according to the relative change between 'before' and 'due to'.

Table A1: Frontier technology shares over time (numbers to Figure 1)

	Office & Communication				Production			
	Survey 2016		Survey 2021		Survey 2016		Survey 2021	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2011	5.78%				3.68%			
2016	7.80%	7.80%	5.71%		5.07%	5.07%	3.54%	
2021		13.43%	8.68%	8.68%		7.89%	4.20%	4.20%
2026				14.74%				6.14%
	actual 2011-2016	planned 2016-2021	actual 2016-2021	planned 2021-2026	actual 2011-2016	planned 2016-2021	actual 2016-2021	planned 2021-2026
Δ	2.02pp	5.64pp	2.96pp	6.06pp	1.39pp	2.82pp	0.66pp	1.94pp

Notes: The table displays the share of work equipment that respondents classified as frontier technology (see Table 1), averaged across all firms in each survey wave using sampling weights. The interviews for the 2021 survey were largely carried out in 2022 so that, strictly speaking, the length of the solid line 2016–2021 is 5.64 years on average. The left-most and right-most points of each line are based on respondents' recollections and expectations, respectively.

Table A2: Descriptive statistics (by characteristics of main investment in office & communication equipment)

	None		*Before*		*During, not due to*		*Due to*	
	Mean (1)	SD (2)	Mean (3)	SD (4)	Mean (5)	SD (6)	Mean (7)	SD (8)
Firm size								
0-9 employees	78%		70%		55%		60%	
10-49 employees	18%		21%		28%		31%	
50-199 employees	3%		7%		13%		8%	
200+ employees	0%		2%		5%		1%	
Sector								
Manuf. knowledge intensive	1%		2%		3%		2%	
Manuf. non-knowledge intensive	23%		18%		28%		13%	
Services knowledge intensive	19%		29%		16%		26%	
Services non-knowledge intensive	56%		47%		44%		57%	
Information & com. technology	1%		4%		8%		2%	
East Germany	21%		20%		15%		16%	
Covid affectedness								
Severe supply chain problems	54%		57%		57%		51%	
Decline in product demand	24%		30%		37%		35%	
Applied for covid-19 support	37%		28%		47%		17%	
Severe uncertainty	29%		39%		47%		54%	
Decline in revenues	23%		17%		20%		26%	
Covid-19 hosp. rate 2020	0.05	0.02	0.05	0.02	0.05	0.02	0.05	0.03
Δ log industry revenue (during)	0.00	0.15	-0.03	0.21	-0.08	0.21	0.01	0.11
Δ log industry revenue (pre)	0.13	0.11	0.13	0.10	0.11	0.13	0.07	0.12
#weeks forced closure	5	11	6	16	7	12	5	9
Log #weeks forced closure	0.67	1.21	0.71	1.35	1.08	1.40	0.78	1.26
Technology share (before Covid)								
Manual technology (1.0/2.0)	46%	29%	35%	21%	44%	27%	46%	21%
Digital technology (3.0)	54%	29%	51%	21%	46%	25%	44%	16%
Frontier technology (4.0)	0%	3%	14%	17%	10%	17%	10%	12%
Remote work								
Initial share of remote work	5%	14%	11%	25%	9%	15%	8%	12%
Remote work potential	0.38	0.20	0.50	0.17	0.37	0.20	0.50	0.18
Log remote work potential	-1.13	0.57	-0.77	0.41	-1.14	0.60	-0.79	0.44
Employees' education								
No vocational training	5%	14%	5%	14%	8%	19%	7%	13%
Vocational training	77%	31%	64%	34%	68%	31%	61%	39%
University degree	15%	27%	30%	35%	21%	30%	31%	37%
Employees' job skill level								
Helpers/assistants	14%	27%	10%	18%	18%	24%	6%	13%
Skilled employees	66%	36%	59%	36%	56%	30%	72%	25%
Specialists	10%	22%	13%	23%	17%	23%	8%	13%
Experts	10%	22%	18%	31%	9%	17%	14%	19%
AKM firm fixed effect	-0.09	0.19	-0.04	0.21	-0.05	0.20	-0.14	0.22
Observations	1,150		789		224		105	

Notes: Statistics are calculated using sampling weights. See also the notes to Table 2.

Table A3: Decomposition of changes in frontier technology shares by characteristics of main investment

	Share of firms	Δ frontier technology share	% of overall change	Obs.
	(1)	(2)	(3)	(4)
A: Frontier investments in office & communication equipment				
None	70.1	-0.2	-5.2	1,150
Before	22.3	10.8	80.0	789
During, not due to	3.9	7.8	10.3	224
Due to	3.7	12.0	15.0	105
Total	100.0	3.0	100.0	2,268
B: Frontier investments in production equipment				
None	87.8	-0.0	-0.1	1,060
Before	11.1	4.6	84.2	237
During, not due to	1.0	8.5	14.3	49
Due to	0.0	19.8	1.5	5
Total	100.0	0.6	100.0	1,351

Notes: 'Δ frontier technology share' is the average change in the frontier technology share within each investment category. '% of overall change' is the percentage share this category amounts to in the overall change in the share of frontier technologies, that is, the product of 'Share of firms' and 'Δ frontier technology share' divided by the total (average) change observed. All statistics other than number of observations are calculated using sampling weights.

Table A4: Decomposition of changes in frontier technology shares by characteristics of main investment—employment-weighted

	Share of firms	Δ frontier technology share	% of overall change	Obs.
	(1)	(2)	(3)	(4)
A: Frontier investments in office & communication equipment				
None	50.7	-0.2	-2.1	1,150
Before	33.3	10.1	71.2	789
During, not due to	9.6	8.9	17.9	224
Due to	6.4	9.6	13.0	105
Total	100.0	4.7	100.0	2,268
B: Frontier investments in production equipment				
None	74.4	-0.0	-0.1	1,060
Before	22.5	7.7	86.3	237
During, not due to	2.8	8.5	11.7	49
Due to	0.4	11.9	2.1	5
Total	100.0	2.0	100.0	1,351

Notes: 'Δ frontier technology share' is the average change in the frontier technology share within each investment category. '% of overall change' is the percentage share this category amounts to in the overall change in the share of frontier technologies, that is, the product of 'Share of firms' and 'Δ frontier technology share' divided by the total (average) change observed. All statistics other than number of observations are calculated using sampling weights multiplied by baseline employment.

Table A5: Changes in frontier technology shares by investment characteristics—production equipment

	Change in frontier technology share				
	2016–21				2021–26
	Retrospective		Actual	Planned	Planned
	(1)	(2)	(3)	(4)	(5)
A: Before, during, due to (main and secondary investments)					
Before	7.68***	7.11***	-1.57	3.08	6.01***
	(1.50)	(2.26)	(4.82)	(2.44)	(1.63)
During, not due to	5.79***	3.51	9.68**	-3.07	-2.32
	(1.49)	(2.46)	(4.73)	(2.17)	(3.79)
Due to	13.1***	-1.70	-28.4***	12.1**	7.70
	(4.88)	(2.82)	(6.55)	(5.92)	(6.72)
R-squared (adjusted)	0.44	0.35	0.65	0.66	0.20
B: Main vs. secondary					
Main	7.87***	6.97***	-0.45	2.96	6.92***
	(1.39)	(2.50)	(5.34)	(2.78)	(1.55)
Secondary	5.11***	3.50	8.31	-2.98	-6.21
	(1.78)	(3.18)	(6.29)	(2.62)	(4.05)
R-squared (adjusted)	0.45	0.34	0.64	0.66	0.23
C: Before, during, due to (only main investments)					
Before	8.13***	9.16***	-0.21	2.54	6.14***
	(1.62)	(2.78)	(5.60)	(2.92)	(1.57)
During, not due	8.76***	6.90***	9.16	0.17	7.54***
	(1.92)	(2.09)	(6.12)	(2.17)	(1.79)
Due to	18.8***	-2.76	-31.5***	13.3**	11.4
	(5.70)	(3.02)	(7.00)	(5.66)	(9.97)
R-squared (adjusted)	0.41	0.33	0.65	0.66	0.21
Observations	1,351	201	201	201	1,351
Mean of dependent variable	0.6	0.2	0.9	3.4	1.6
Panel firms only		✓	✓	✓	

Notes: The table reports results from regressing changes in frontier shares on the right-hand-side variables listed in the left-most column—indicating the presence of investments with the stated characteristics—as well as controls. Non-investors are the excluded category in each case. Controls include baseline technology shares, industry dummies (10 categories), firm size dummies (4 categories), federal state dummies (16 categories) interacted with urban status, dummies for the month of interview (10 categories), remote work use before pandemic, initial employee education (3 categories), initial employee job requirement levels (4 categories), and AKM firm fixed effects. Regressions are weighted using sampling weights (cross-sectional or longitudinal as appropriate). Robust standard errors in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

Table A6: Changes in frontier technology shares by investment characteristics—office & communication equipment, weighted by employment

	Change in frontier technology share				
	2016–21				2021–26
	Retrospective		Actual	Planned	Planned
	(1)	(2)	(3)	(4)	(5)
A: Before, during, due to (main and secondary investments)					
Before	9.49***	9.13***	13.0***	5.04***	5.54***
	(0.77)	(2.17)	(3.24)	(1.82)	(1.09)
During, not due to	4.16***	4.29**	9.72**	-1.29	2.87**
	(1.00)	(1.90)	(3.94)	(2.41)	(1.20)
Due to	3.21***	5.29**	5.59	0.43	1.49
	(1.12)	(2.23)	(3.63)	(2.14)	(1.09)
R-squared (adjusted)	0.34	0.40	0.60	0.18	0.13
B: Main vs. secondary					
Main	11.6***	11.9***	12.8***	4.46**	6.91***
	(0.85)	(1.75)	(3.64)	(1.98)	(1.31)
Secondary	1.50	1.89	7.22**	0.095	1.42
	(1.20)	(2.01)	(3.25)	(2.16)	(1.18)
R-squared (adjusted)	0.36	0.41	0.59	0.17	0.14
C: Before, during, due to (only main investments)					
Before	12.8***	12.9***	16.6***	6.02***	7.85***
	(0.76)	(1.66)	(3.41)	(2.08)	(1.24)
During, not due	11.0***	12.7***	16.9**	0.51	5.82***
	(1.26)	(2.45)	(6.61)	(3.20)	(1.68)
Due to	12.6***	14.3***	18.6***	2.21	9.52***
	(1.57)	(4.44)	(5.28)	(3.12)	(1.79)
R-squared (adjusted)	0.36	0.41	0.58	0.19	0.15
Observations	2,268	388	388	388	2,268
Mean of dependent variable	4.7	4.1	-0.7	4.6	8.2
Panel firms only		✓	✓	✓	

Notes: The table reports results from regressing changes in frontier technology shares on the right-hand-side variables listed in the left-most column—indicating the presence of investments with the stated characteristics—as well as controls. Non-investors are the excluded category in each case. Controls include baseline technology shares, industry dummies (10 categories), firm size dummies (4 categories), federal state dummies (16 categories) interacted with urban status, dummies for the month of interview (10 categories), remote work use before pandemic, initial employee education (3 categories), initial employee job requirement levels (4 categories), and AKM firm fixed effects. Regressions are weighted using sampling weights (cross-sectional or longitudinal as appropriate) multiplied by baseline employment. Robust standard errors in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

Table A7: Changes in frontier technology shares by investment characteristics—OCE, robustness to hidden during-not-due-to investments

	Δ frontier technology share, retrospective			
	(1)	(2)	(3)	(4)
Before	12.5***	12.5***	12.6***	12.5***
	(1.55)	(1.53)	(1.50)	(1.59)
During, not due to	1.70			
	(1.47)			
Due to	5.00***	4.02*	4.45**	4.78**
	(1.81)	(2.11)	(1.89)	(1.91)
During, not due to (alternative I)		2.61		
		(1.59)		
During, not due to (alternative II)			3.30**	
			(1.45)	
During, not due to (alternative III)				0.94
				(1.54)
Observations	2,268	2,268	2,268	2,268
R-squared (adjusted)	0.41	0.41	0.41	0.40
Mean of dependent variable	3.0			

Notes: The table reports results from regressing changes in frontier technology shares on investment characteristics. Non-investors are the excluded category. Alternatives I-III refer to all possible cases of hidden during-not-due-to investments. Controls include baseline technology shares, industry dummies (10 categories), firm size dummies (4 categories), federal state dummies (16 categories) interacted with urban status, dummies for the month of interview (10 categories), remote work use before pandemic, initial employee education (3 categories), initial employee job requirement levels (4 categories), and AKM firm fixed effects. Regressions are weighted using sampling weights (cross-sectional or longitudinal as appropriate). Robust standard errors in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

Table A8: Actual versus counterfactual change in frontier technology share—production equipment

	Actual change	Counterfactual change based on	
	Regression-based decomposition	Before investments	Planned investments
	(1)	(2)	(3)
Baseline (no investment)	−0.53	−0.53	–
Before	0.89	0.89	*1.77*
During not due	0.23	*0.53*	*1.05*
Due to	0.01		
Full period	0.60	*0.90*	2.82

Notes: Column (1) displays a decomposition based on the estimated equation (1),

$$\overline{\Delta_{2016,2021} \text{ Frontier technology share}_i} = \widehat{\lambda_1} \times \overline{\text{Before}_i} + \widehat{\lambda_2} \times \overline{\text{During, not due}_i} + \widehat{\lambda_3} \times \overline{\text{Due to}_i} + \widehat{\beta} \times \overline{X_i},$$

where bars indicate sample means and hats represent OLS estimates, as reported in Tables 3 and A5. That is, each row reports a product of an estimated coefficient and its corresponding sample mean, with the first row referring to the prediction based on the controls X_i. Column (2) extrapolates the estimated change from column (1) for before investments to the period during the pandemic. Column (3) distributes the planned investments for the whole period as reported in Figure 1 to the period before and during the pandemic but without having an explicit prediction in the first line of what happens to non-investors. All extrapolations (in italics) attribute 63% (37%) of the overall change to the before (during) period given that the before period was on average approximately 3.54 years, while the average period during the pandemic was 2.11 years long.

Table A9: Applications of due-to investments and employment

	Δ employees working from home in %		Δ log employment × 100		Δ share of employment not liable to social security in %		Employees in short-time work in 2021 in %	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IT infrastructure for remote work	25.2***	25.9***	2.73	1.49	3.12	3.78	1.48	2.46
	(5.92)	(5.91)	(11.4)	(11.6)	(2.98)	(3.22)	(3.92)	(3.29)
Basic IT infrastructure	19.6*	17.7**	41.1***	38.4***	3.26	3.71	-7.04	-1.86
	(10.3)	(8.23)	(13.8)	(10.6)	(5.13)	(4.58)	(11.9)	(8.11)
Business management and planning tools	23.0	19.8	16.9	18.7	20.6	21.0	11.0	7.60
	(16.0)	(12.3)	(17.0)	(17.6)	(18.5)	(19.6)	(14.2)	(12.8)
Cloud computing infrastructure	47.8***	45.7***	7.66	8.99	7.16**	6.97***	-14.1***	-7.58
	(9.08)	(8.72)	(16.2)	(15.5)	(2.97)	(2.25)	(4.86)	(5.72)
Communication and collobaration tools	21.5**	21.0**	13.4	11.0	-2.40	-1.33	-1.12	0.29
	(9.33)	(8.86)	(9.43)	(10.7)	(4.33)	(4.41)	(5.97)	(5.43)
Data analytics and visualization	19.9**	20.0**	4.22	3.62	-4.12	-2.87	-0.011	1.94
	(9.37)	(8.11)	(12.1)	(13.7)	(4.68)	(4.31)	(5.81)	(5.47)
E–commerce and customer interaction	1.84	-0.24	-3.38	-3.56	-0.79	1.46	-5.19	-8.54
	(5.83)	(5.68)	(9.07)	(10.2)	(4.39)	(4.60)	(10.0)	(7.07)
Process automation	3.76	5.90	-14.7	-16.8	-3.28	-1.42	-4.88	-14.0
	(11.8)	(11.7)	(11.6)	(11.1)	(3.60)	(3.18)	(10.1)	(14.4)
Observations	2,214	2,214	2,244	2,244	2,244	2,244	2,145	2,145
R-squared	0.35	0.40	0.16	0.21	0.12	0.15	0.26	0.40
Mean of dependent variable	15.0	15.0	-4.7	-4.7	-2.4	-2.4	10.9	10.9
Covid controls		✓		✓		✓		✓

Notes: The table reports results from regressing changes in employment indicators 2019–2021 on dummies for having invested in certain technology categories due to the pandemic. Controls include a dummy for any other investment due to the pandemic (without stating a specific technology), dummies for having invested in frontier technology before or during (though not due to) the pandemic, baseline technology shares, industry dummies (10 categories), firm size dummies (4 categories), federal state dummies (16 categories) interacted with urban status, dummies for the month of interview (10 categories), remote work use before the pandemic, initial employee education (3 categories), initial employee job requirement levels (4 categories). Investments in product design, development, and management are not shown in the table because such an investment did not occur due to the pandemic. 'Covid controls' include the variables shown in Table A10. Regressions are weighted using sampling weights. Robust standard errors in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

Table A10: Firm-level Covid exposure and investments in office & communication equipment

	Reason & timing			*Change in frontier technology share*				
			During,	2016–21				2021–26
	Due to	Pre	not due to	Retrospective		Actual	Planned	Planned
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log #weeks forced closure	1.54	-0.099	1.41*	0.14	0.48	-0.20	-0.64	-0.13
	(1.63)	(1.70)	(0.84)	(0.44)	(0.69)	(1.03)	(0.64)	(0.48)
Severe supply chain problems	-0.00088	5.43	-0.68	0.016	0.86	1.12	-1.59	-1.23
	(2.80)	(3.46)	(2.04)	(0.70)	(1.19)	(1.74)	(1.51)	(1.41)
Decline in product demand	-1.98	3.88	1.81	-0.79	1.96	3.83	-3.55	1.86
	(3.40)	(5.16)	(2.97)	(0.97)	(1.81)	(2.70)	(2.54)	(1.53)
Applied for covid-19 support	-5.62**	-5.50	1.94	-1.90**	-6.33***	-8.50***	0.71	1.46
	(2.45)	(4.30)	(2.22)	(0.86)	(1.86)	(2.78)	(1.67)	(1.53)
Severe uncertainty	5.76*	5.57	0.88	-0.29	-3.53**	-5.39**	6.68***	3.07*
	(3.44)	(4.01)	(2.09)	(0.82)	(1.63)	(2.21)	(1.94)	(1.59)
Decline in revenues	0.44	-0.43	-5.89**	-0.24	6.19***	0.99	1.28	-1.27
	(2.91)	(4.26)	(2.43)	(0.91)	(1.53)	(2.54)	(1.72)	(1.85)
Log remote work potential	2.70	13.3***	-0.28	2.91***	4.01***	-0.062	4.87***	4.03***
	(2.57)	(3.70)	(2.58)	(0.87)	(1.28)	(1.86)	(1.64)	(1.30)
Δ log industry revenue (during)	16.1*	2.18	-27.0***	-2.03	1.76	-6.43	14.7	6.06*
	(8.62)	(10.6)	(10.1)	(2.73)	(6.20)	(8.96)	(13.9)	(3.56)
Covid-19 hosp. rate 2020	10.3	83.2	78.4*	36.5***	-25.5	51.9*	5.71	8.44
	(47.2)	(57.2)	(47.1)	(13.3)	(22.0)	(27.2)	(33.9)	(21.6)
Observations	2,268	2,268	2,268	2,268	388	388	388	2,268
R-squared (adjusted)	0.19	0.35	0.21	0.12	0.68	0.64	0.44	0.14
Mean of dependent variable	10.2	25.6	7.6	3.0	2.4	-2.4	4.9	5.7
Panel firms only					✓	✓	✓	

Notes: The table reports results from regressing investment outcomes on pandemic-related variables. Controls include pre-Covid industry-level revenue growth, baseline technology shares, industry dummies (10 categories), firm size dummies (4 categories), federal state dummies (16 categories) interacted with urban status, dummies for the month of interview (10 categories), remote work use before the pandemic, initial employee education (3 categories), initial employee job requirement levels (4 categories). Regressions are weighted using sampling weights (cross-sectional or longitudinal as appropriate), and AKM firm fixed effects. Coefficients in columns (1)-(3) have been multiplied by 100. Robust standard errors in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

Table A11: Firm-level Covid exposure and investments in office & communication equipment (employment weights)

	Reason & timing			*Change in frontier technology share*				
			During,	2016–21				2021–26
	Due to	Pre	not due to	Retrospective		Actual	Planned	Planned
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log #weeks forced closure	0.70	0.085	1.66	-0.42	0.46	2.40*	-0.10	0.21
	(1.40)	(1.74)	(1.55)	(0.44)	(0.92)	(1.39)	(0.92)	(0.51)
Severe supply chain problems	0.0075	9.62***	-0.13	0.38	0.79	-2.21	-3.32**	-0.98
	(3.01)	(3.41)	(2.64)	(0.65)	(1.45)	(2.94)	(1.61)	(1.33)
Decline in product demand	-3.21	-0.66	4.03	-0.26	-0.074	-4.32	-4.31**	1.76
	(3.31)	(3.96)	(3.49)	(0.94)	(1.86)	(3.83)	(1.83)	(1.27)
Applied for covid-19 support	-5.04	-3.04	0.83	-0.72	-4.43***	-7.84**	-0.26	-1.55
	(3.32)	(3.77)	(3.22)	(0.96)	(1.62)	(3.22)	(1.71)	(1.01)
Severe uncertainty	6.15**	5.35	-1.65	-0.22	-0.13	-2.35	1.97	1.37
	(2.98)	(3.35)	(2.60)	(0.65)	(1.72)	(2.92)	(1.57)	(1.01)
Decline in revenues	0.76	6.51	-4.00	-0.48	-0.47	3.45	1.24	1.12
	(3.47)	(4.49)	(3.74)	(0.91)	(2.05)	(3.83)	(2.01)	(1.27)
Log remote work potential	10.3**	20.4***	4.11	5.34***	3.53**	0.56	7.71***	2.44*
	(4.72)	(4.31)	(4.23)	(1.57)	(1.66)	(3.85)	(2.62)	(1.47)
Δ log industry revenue (during)	22.1**	-0.41	-7.08	-5.31	-0.27	-19.8	4.67	6.14
	(9.37)	(12.1)	(10.3)	(3.34)	(6.43)	(12.8)	(6.98)	(4.08)
Covid-19 hosp. rate 2020	-7.12	33.2	186.4***	15.2	-13.7	48.6	32.4	-4.74
	(50.5)	(57.5)	(59.1)	(11.2)	(28.2)	(46.1)	(28.6)	(19.0)
Observations	2,268	2,268	2,268	2,268	388	388	388	2,268
R-squared (adjusted)	0.19	0.29	0.15	0.14	0.18	0.53	0.21	0.10
Mean of dependent variable	22.0	42.6	17.7	4.7	4.1	-0.7	4.6	8.2
Panel firms only					✓	✓	✓	

Notes: The table reports results from regressing investment outcomes on pandemic-related variables. Controls include pre-Covid industry-level revenue growth, baseline technology shares, industry dummies (10 categories), firm size dummies (4 categories), federal state dummies (16 categories) interacted with urban status, dummies for the month of interview (10 categories), remote work use before pandemic, initial employee education (3 categories), initial employee job requirement levels (4 categories), and AKM firm fixed effects. Regressions are weighted using sampling weights (cross-sectional or longitudinal as appropriate) multiplied by baseline employment. Coefficients in columns (1)-(3) have been multiplied by 100. Robust standard errors in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

Table A12: Firm-level Covid exposure and investments in production equipment

	Reason & timing			*Change in frontier technology share*				
			During,	2016–21				2021–26
	Due to	Pre	not due to	Retrospective		Actual	Planned	Planned
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log #weeks forced closure	-0.022	2.03*	-0.95	-0.17*	-0.12	2.65***	0.58	0.91
	(0.036)	(1.20)	(0.66)	(0.10)	(0.22)	(0.75)	(0.46)	(0.62)
Severe supply chain problems	0.22	7.37**	-0.56	0.063	-0.87	1.06	-0.50	-0.56
	(0.14)	(3.00)	(2.05)	(0.34)	(0.86)	(2.56)	(1.40)	(0.82)
Decline in product demand	0.053	-0.68	0.60	-0.48	0.95	-3.57	1.27	0.81
	(0.092)	(2.98)	(1.73)	(0.42)	(0.75)	(2.47)	(1.58)	(1.05)
Applied for covid-19 support	-0.13	-1.53	-0.29	0.036	0.81	-2.56	-1.98	-0.83
	(0.11)	(2.59)	(1.71)	(0.35)	(0.57)	(2.07)	(1.37)	(0.64)
Severe uncertainty	-0.14	-2.21	4.87**	0.17	-0.029	0.65	0.87	0.38
	(0.15)	(3.04)	(2.15)	(0.29)	(0.74)	(1.98)	(1.34)	(0.96)
Decline in revenues	-0.033	-1.45	-0.34	0.59	-0.84	5.80*	2.36*	-0.56
	(0.10)	(3.72)	(1.88)	(0.77)	(0.78)	(3.22)	(1.21)	(0.94)
Log remote work potential	-0.099	1.97	-0.12	0.47	-0.14	0.32	-3.22**	1.12*
	(0.097)	(3.85)	(1.22)	(0.44)	(0.74)	(3.57)	(1.56)	(0.67)
Δ log industry revenue (during)	0.030	4.37	3.64	0.94	-2.37	-2.18	0.54	-1.94
	(0.93)	(10.7)	(5.41)	(1.15)	(5.02)	(11.6)	(6.89)	(2.95)
Covid-19 hosp. rate 2020	-1.89	36.3	2.11	3.14	7.41	30.9	15.7	0.33
	(1.20)	(39.9)	(21.8)	(5.31)	(12.0)	(43.7)	(29.2)	(9.51)
Observations	1,351	1,351	1,351	1,351	201	201	201	1,351
R-squared (adjusted)	-0.02	0.53	0.45	0.08	0.06	0.68	0.73	0.19
Mean of dependent variable	0.1	11.7	3.9	0.6	0.2	0.9	3.4	1.6
Panel firms only					✓	✓	✓	

Notes: The table reports results from regressing investment outcomes on pandemic-related variables. Controls include pre-Covid industry-level revenue growth, baseline technology shares, industry dummies (10 categories), firm size dummies (4 categories), federal state dummies (16 categories) interacted with urban status, dummies for the month of interview (10 categories), remote work use before pandemic, initial employee education (3 categories), initial employee job requirement levels (4 categories), and AKM firm fixed effects. Regressions are weighted using sampling weights (cross-sectional or longitudinal as appropriate). Coefficients in columns (1)-(3) have been multiplied by 100. Robust standard errors in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

B Data

B.1 BIZA II survey design

This section provides details on the design of the IAB-IZA-ZEW Labor Market 4.0-Establishment Survey (BIZA II) and its link to the earlier survey (BIZA I).

Sampling, non-response, and field phase. The survey population consists of establishments (henceforth *firms*) in Germany with at least one employee subject to social insurance contributions. We distinguish two groups: panel firms and first respondents. 2,032 panel firms participated in the first wave of the survey (BIZA I) in 2016. However, due to firm closures or lack of employees subject to social insurance contributions, the number of panel firms fell to 1,595, with 469 actually responding in BIZA II.

Contact information for both groups was drawn from the establishment file of the German Federal Employment Agency at cutoff-date June 30, 2020 (Betriebe-Quartalsdatei 202106, Nürnberg 2022) according to the sampling plan of BIZA I.[41] The survey company sent written invitations to participate in the survey to 27,286 firms by post. The invitations contained information about the content and purpose of the study as well as data protection measures. The purpose of the study was stated as research on the effects of the pandemic on establishments in connection with frontier technology use and adoption. The invitations further stated that the survey company would soon contact the firms via phone.

Table B1 breaks down the original sample by type of response. 4,136 firms were neutral failures, meaning they could not be reached, for instance due to incorrect contact details or because they had been shut down. Of the remaining 23,132 firms (hereafter referred to as the corrected sample), 3,003 firms successfully completed the interview, yielding a response rate of 13%.

Whenever firms declined the interview, the survey company asked for the reason. This allows us to investigate whether selective non-response may bias our findings. Fortunately, lack of interest in the topic of the study—which may arise if frontier technologies do not play an important role in a firm—accounts for only 5 percent of the corrected sample. We further demonstrate below that the appropriately re-weighted survey sample is representative of the population.

The 3,003 successful interviews were conducted by 61 interviewers in computer-assisted telephone interviews (CATI) with either the firm's production or general manager. On average, the interviews lasted 30 minutes and took place between October 2021 and July 2022. Figure B1 shows the distribution of interview dates.

[41] The stratification by sector (5 categories), firm size (4 categories) and location (East or West Germany) results in 40 cells. The survey company conducting the survey had a target of at least 75 interviews in each of the 40 cells.

Table B1: Response rates

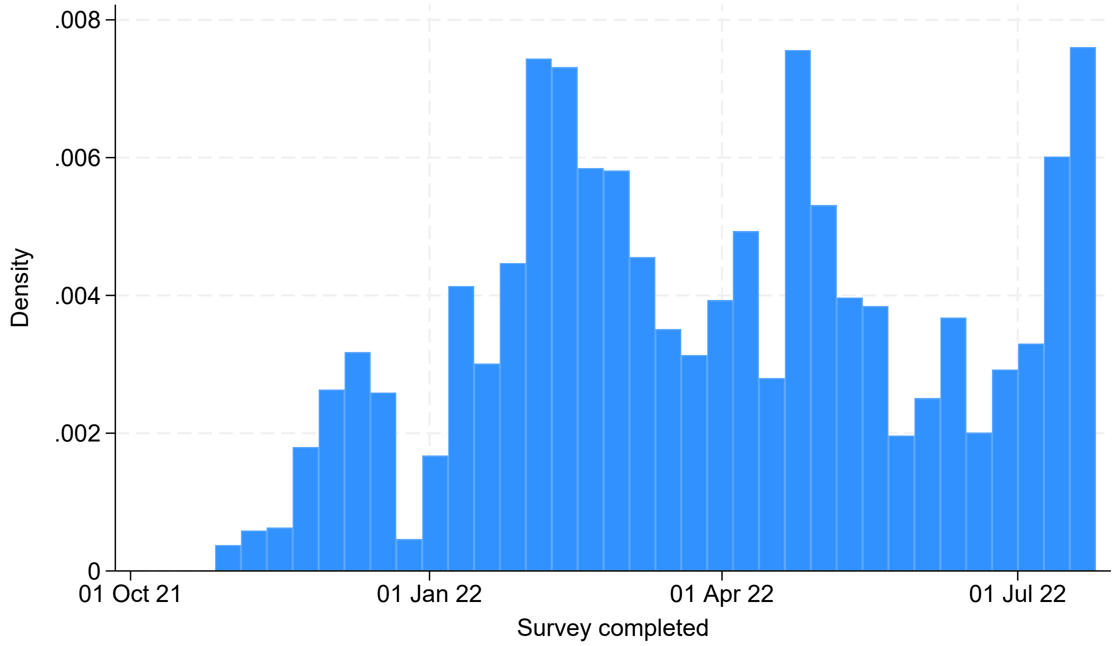
	Count	In % of original sample	In % of corrected sample
Sample of firms contacted	**27,268**	**100%**	
Neutral failures	**4,136**	**15.17**	
Not a firm	345	1.27	
Fax/no dial tone/no connection	2,266	8.31	
Wrong firm	1,067	3.91	
Firm was shut down	161	0.59	
No response after 10+ attempts	297	1.09	
Corrected sample (w/o neutral failures)	**23,132**	**84.83**	**100.00**
Abandoned after contact (15+ attempts)	2,534	9.29	10.95
Cancellations by email/phone	677	2.48	2.93
Information refused without reason	1,370	5.02	5.92
Generally no participation in surveys	2,885	10.58	12.47
No interest in the topic of the study	1,166	4.28	5.04
No time	1,090	4.00	4.71
No access to the target person	1,279	4.69	5,53
Failure to schedule appointment	2,148	7.87	9.28
Other	740	2,71	3,20
No answer	6,211	22.78	26.85
Started interviews with target person	**3,032**		**13.11**
Completed interviews	3,003		12.98
Aborted interviews	29		0.13

Weights. Our sample is stratified by firm size (four categories), industrial sector (five categories), and region (East/West Germany) and covers both service and manufacturing firms. To ensure sufficient observations, we conducted about 80 interviews for each of the resulting 36 cells.[42] This naturally leads to oversampling of certain cells relative to the entire population of firms. We correct for it by computing firm stratification weights w_f as the inverse inclusion probability of firms in our survey. Weights are scaled such that the sum of weights equals the number of firms interviewed, 3,003.[43] We use these weights whenever we focus on the average firm. In order to study the average worker, we alternatively apply employment weights s_f. In particular, we use the firm stratification weights w_f to compute the employment weights $s_f = w_f n_f$, where n_f is the

[42]We aggregate seven cells with small number of observations to three cells (for instance, for firms with 50–200 employees and 200 or more employees in the East German ICT sector due to the small number of large ICT firms in East Germany).

[43]The sample of firms was drawn in 2020. Weights are therefore representative of the 2020 firm distribution and time-constant.

Figure B1: Distribution of interview dates



firm's total employment. We apply the employment-weighted firm stratification weights s_f in empirical analyses which are meant to be representative of the German workforce.

Representativeness. Table B2 compares major characteristics of the unweighted and weighted survey sample with the corresponding characteristics of the population. To do so, we use the IAB employment history for the year 2020 (IAB Beschäftigtenhistorik (BeH) V10.08.00-202112, Nürnberg 2023). As of June 30, 2020, we are able to identify 2,942 firms (out of a total of 2,985 firms that we find in the administrative data in our observation period). The table displays only minor differences in the stratification variables of sector, firm size, and firm location between the population of firms and the stratification-weighted survey data.

Table B2 also considers workforce characteristics beyond the stratification variables. The female share is almost identical in the survey and the entire firm population. Concerning the educational composition, the survey firms have a 4 percentage points higher share of university graduates and a 5 points lower share of unskilled workers. There are also only minor differences with regard to the age structure. Altogether, given the similarity between the survey and the population, we are confident that our sample of firms is broadly representative of German firms.

Table B2: Characteristics of the entire German firm population and the surveyed firms

	Entire firm population (1)	Survey firms weighted (2)	Survey firms unweighted (3)
Firm characteristics			
Share of firms by sector:			
Non-knowledge intensive production	0.19	0.21	0.21
Knowledge intensive production	0.01	0.01	0.20
Non-knowledge intensive service	0.58	0.53	0.22
Knowledge intensive service	0.20	0.22	0.21
ICT	0.02	0.03	0.16
Share of firms by firm size:			
0-9 emp	0.83	0.79	0.30
10-49 emp.	0.13	0.17	0.28
50-199 emp.	0.03	0.03	0.26
200 and more emp.	0.01	0.01	0.16
East Germany	0.18	0.19	0.47
Workforce characteristics			
Female share	0.56	0.57	0.42
Share of workers by education:			
No vocational training/miss.	0.22	0.17	0.13
Vocational training	0.65	0.65	0.63
University degree	0.14	0.18	0.24
Share of workers by age category:			
Age <30 years	0.18	0.20	0.18
Age 30-49 years	0.39	0.42	0.44
Age 50 or older	0.43	0.39	0.38
Number of firms	2,589,153	2,942	2,942

Notes: This table shows key characteristics for the entire population of German firms and the firm sample for the year 2020, both unweighted and weighted. The numbers in Column (2) are weighted with firm stratification weights.

B.2 Supplemental shock measures and remote work potential

We asked for direct exposure measures to the pandemic in the survey, including how many weeks the firm had to close operations, uncertainty about future infection rates, changes in product demand and revenues, whether the firm was affected by supply chain bottlenecks, and whether it applied for Covid-19 government support. We also compute revenue changes in the firm's main industry as another exposure measure. The idea in the latter is that the pandemic may have impacted firms at the level of their industries, affecting demand for industry-specific goods and services or shocking supply via production restrictions and changing availability of intermediate goods which are necessary inputs in that industry. We do this by aggregating firm-level revenues from financial accounts data provided by Bureau van Dijk (BvD) to the 2-digit industry level (82 unique values).[44]

The remote work potential (RWP) variable we employ was developed by Bruhns et al. (2024). It uses information on 73 working conditions listed in BERUFENET for each individual occupation.[45] Working conditions are assessed in terms of whether they are rather conducive, not relevant, or rather obstructive to performing the occupation's activities in a flexible location (working from home or mobile work). This results in a measure between "0" and "+1" for each individual occupation. The measure is merged to employee data in 2019 via the occupation code (KldB-2010, 5-digit) and is aggregated to the firm level via its employment composition. Hence, a firm's RWP is the average remote work potential of its employees' occupations. The employee data is based on records from the employment biographies (BeH) V10.06.

B.3 Administrative labor market data

We link our survey data to employment biographies from social security records (IAB Integrierte Erwerbsbiografien (IEB) V17.00.00-202212, Nürnberg 2023) of all workers employed in the surveyed firms between 2016 and 2021 from 1999 onward. The IEB covers the universe of German employees liable to social security contributions, benefit recipients, unemployed searching for employment, and participants in active labor market policy measures, thus excluding self-employed, civil servants, and students. The IEB include, among others, information on workers' employment status, daily wages[46], occupation and industry. We use this data (4,895,096 observations for 661,132 employees) to study employment changes at the firm level. For this, we calculate the overall employment for the years 2019–2021 as the total number of full-time equivalent working days of all employees within a firm and calendar year.[47]

In order to obtain firm characteristics that serve as controls in later analyses, we further use employment spells from social insurance records (IAB Beschäftigtenhistorik

[44]The widely-used BvD data allow us to compute revenue changes also for industries that are commonly not reported in aggregate business survey data like Eurostat's Structural Business Statistics (SBS). These non-reported industries are mainly in the primary sector and in specific services, social, and entertainment industries. Reassuringly, for those industries where both sources are available, revenues from BvD and SBS are highly correlated (e.g., see also Böhm and Qendrai, 2023).

[45]BERUFENET is an online database of the German Federal Employment Agency that contains descriptions of occupational requirements at the 5-digit level of the occupational classification (KldB, 2010). It is used by local employment agencies for career advice and job placement, and serves the public more broadly as a free online database for career orientation.

[46]Wages are reported only up to the social security contribution limit. We impute top-coded wages using Tobit regressions following Dustmann et al. (2009) and Card et al. (2013).

[47]The data does not include exact working hours but only full-time / part-time indicators. We weight part-time days by 0.5.

(BeH) V10.08.00-202212, Nürnberg 2023). We focus on prime-age workers employed in the surveyed establishments on June 30th in the years 2016–2022 (e.g., for 2016 these are approximately 280,000 workers in 2,671 survey firms). For this sample, we calculate yearly indicators of the firm's workforce composition by *job requirements* level. This differentiates four levels of complexity within a given occupation independent of the nature of the specific work activities performed: (1) unskilled workers, (2) professionals, (3) specialists, and (4) experts. Regarding education groups, we distinguish between (1) no apprenticeship qualification, (2) apprenticeship qualification and (3) graduates from a university or technical college. We also use the administrative data for information on industry (10 categories), firm size (4 categories), and firm location (16 federal state dummies, urban/rural region).

Finally, short-time work data are drawn from so-called Statistik Realisierte Kurzarbeit - Stichprobenziehung des IAB (BTR KuG) V01.00.00 - 202306. This contains, besides others, information on the approval period for short-time work allowances and the firm's total number of employees in short-time work. Details of the STW scheme during the Covid-19 crisis are discussed in Drahokoupil and Müller (2021). The maximum duration was extended from 12 to 24 months. In addition, for workers with a reduction of working time of more than 50%, the replacement rate increased from 60% (67%) to 70% (77%) for employees without (with) children after three months, and to 80% (88%) after six months of benefit receipt. Hence, job separations remained low among regular employed and the number of jobs subject to social insurance contributions declined by 1.6% only despite a drop in total working hours by almost 6% (Gartner et al., 2022). By contrast, workers in marginal employment were not covered by STW and thus experienced a much higher job separation rate.

B.4 Classifying technologies by application

To classify frontier technologies by application, we followed a supervised machine learning approach. We first extracted descriptions of all technologies mentioned by firms using ChatGPT. In total, we obtained a list of 2,983 unique technologies that firms mentioned, including both main and secondary investments. We kept office and communication technologies separate from production technologies during the entire classification procedure.

Respondents named up to three office and up to three production technologies. These include one main investment and up to two secondary investments, respectively. The multiplicity results from follow-up questions about secondary investments during, due to, or before, the pandemic. For each technology named, we asked ChatGPT 3.5 Turbo, using OpenAI API, to provide further information on these technologies. The concrete prompt was "Provide a concise, two-sentence description of the technology word, and describe what it is used for. Answer in the format: word is..." Table B3 gives some examples to demonstrate the quality of these descriptions.

Based on the technology names together with the extracted descriptions, we defined 10 categories in office and communication such as "communication and collaboration tools", " cloud computing" or "basic IT infrastructure". We then created a training dataset where we manually categorized 398 office technologies into our defined categories. Since many technologies were mentioned multiple times throughout the survey, this effectively amounted to classifying 1,229 office technologies.

To classify the remaining office technologies, we then trained a Neural Network Classifier (NNC) to predict the category based on the descriptions from ChatGPT. Descriptions were pre-processed using tokenization, removing stop words and lemmatization before transformation into an input vector. Parameters of the NNC were choosen based on hyperparameter tuning with GridSearch. Note that, compared to only using the technology names themselves, employing the descriptions helps distinguish falsely similar cases like Microsoft Office from Microsoft Cloud. Based on the trained model, we then predict the correct category for all office and communication technologies. We proceed analogously for production technologies. Here, we manually categorized 137 (of all 457) production technologies.

To test the quality of the predictions, we put 50 percent of the manually classified data aside (our test data). We then conducted the prediction and calculated the standard metrics used to evaluate the performance of a classification model, including precision (ratio of true positives to the total number of positive predictions), recall (ratio of true positives to the total number of actual positives), and f1-score (harmonic mean of precision and recall). Overall, the procedure shows a high prediction quality (compare Table B4). For instance, the f1-score is 0.91, which is close to a perfect prediction score of 100%.

To further make transparent what our categories capture, we extracted the 10 most frequent words of each category in Table B5. For instance, the 10 most frequent words in IT infrastructure for remote work include "laptop", "home", "offfice", "notebook", "vpn" or "headset".

Table B3: Examples of technology descriptions extracted from ChatGPT

Example technologies mentioned by respondents	Descriptions extracted from ChatGPT[a]
Artificial intelligence in accounts payable automated invoice verification	Artificial intelligence technology can be used for accounts payable automated invoice verification in order to help businesses save time and money. This technology can help to automate the process of verifying invoices for accuracy and completeness, as well as identifying duplicate invoices and potential fraud.
Chatbot that answers WhatsApp chats automatically	Chatbot technology can be used to automatically answer chats on WhatsApp. This can be used to provide customer support, answer frequently asked questions, or promote a product or service.
Cloud computing and interfaces for evaluation tools	Cloud computing is a type of computing where data and applications are stored on remote servers accessed through the internet. Interfaces for evaluation tools allow users to interact with and evaluate the tools.
Analysis tools for evaluating and forecasting sales activities business data analysis	This technology is used to help businesses analyze and predict sales activity based on past data. This can help businesses make better decisions about pricing, inventory, and marketing strategies.
Teamviewer	Teamviewer is a remote access technology that allows you to control another computer from your own. You can use it to provide remote support or access files and applications on another computer.
3D printer	A 3D printer is a device that creates three-dimensional objects by layering materials based on a digital design. It is used for prototyping, manufacturing, and creating customized objects in various industries such as automotive, aerospace, healthcare, and consumer goods.
Robots for standardized case processing	Robots for standardized case processing is a technology that utilizes automated robots to handle and process standardized cases or tasks, reducing the need for human intervention. It is commonly used in industries such as customer service, healthcare, and finance to streamline and expedite repetitive and rule-based processes.
Bottle inspector detects dirt in bottles	Bottle inspector detects dirt in bottles is an automated technology that uses advanced imaging systems to identify and remove any contaminants or impurities present in bottles during the manufacturing process. It is primarily used in the beverage industry to ensure the cleanliness and quality of bottled products before they are filled and sealed.
Fully automated high-bay warehouse	A fully automated high-bay warehouse is a type of storage facility that uses automated technology to move inventory in and out of the facility. This type of warehouse is often used by businesses that need to store a large amount of inventory in a small space.

[a] We use ChatGPT 3.5 Turbo using OpenAI API. The prompt was "Provide a concise, two-sentence description of the technology {word}, and describe what it is used for. Answer in the format: {word} is.."

Table B4: Evaluation of the classifier's performance on the test set

	precision	recall	f1-score	support
IT infrastructure for remote work	0.97	0.94	0.95	89
Basic IT infrastructure	0.95	0.96	0.95	120
Business management and planning tools	0.85	0.85	0.85	65
Cloud computing instrastructure	0.97	0.98	0.97	98
Communication and collobaration tools	0.92	0.98	0.95	108
Cyber and data security	1.00	0.40	0.57	5
Data analytics and visualization	0.89	0.83	0.86	29
E-commerce and customer interaction	0.93	0.91	0.92	56
Process automation	0.64	0.74	0.69	31
Product design, development, and management	0.75	0.43	0.55	14
Accuracy			0.91	615
Macro avg	0.89	0.80	0.83	615
Weighted avg	0.91	0.91	0.91	615

Table B5: Most frequent words by technology application:

IT infrastructure for remote work	laptop, home, office, accessory, notebook, software, vpn, system, equipment, headset
Basic IT infrastructure	computer, server, software, pc, system, technology, hardware, office, infrastructure, equipment
Business management and planning tools	system, management, erp, software, sap, tool, document, programme, planning, merchandise
Cloud computing infrastructure	cloud, office, system, solution, server, software, service, storage, platform, data
Communication and collaboration tools	team, system, video, communication, telephone, telephony, conference, tool, platform, software
Cyber and data security	system, security, eap, data, firewall, backup, protection, authentication, programme, software
Data analytics and visualization	tool, analysis, data, business, intelligence, analytics, software, system, e.g, evaluation
E-commerce and customer interaction	system, shop, online, platform, internet, crm, customer, portal, tool, management
Process automation	system, software, process, control, production, accounting, billing, data, invoice, tool
Product design, development, and management	system, cad, software, development, scanner, application, product, cam, configurators, platform

C A potential outcomes framework for investments due to the Covid-19 pandemic

Let Y_{i1} denote the increase in the frontier technology share at firm i from 2016–2021. In the absence of the pandemic, the increase would have been Y_{i0} instead. The effect of the pandemic on firm i is $\tau_i = Y_{i1} - Y_{i0}$. Denote the observed increase by Y_i, and since the pandemic is an aggregate event, we have $Y_i = Y_{i1}$ for all i. It is thus challenging to estimate $\tau = \mathrm{E}[\tau_i]$, the average treatment effect (ATE) of the pandemic, our quantity of interest.

Let D_i^P indicate an observed investment *due to* the pandemic. Here we refer to both main and secondary investments. If respondents share our precise understanding of causality, we have that $D_i^P = 1$ is equivalent to $D_{i1}^P = 1$ and $D_i^P = 0$ is equivalent to $D_{i1}^P = 0$. Thus, D_i^P directly identifies the complier (c) population. By definition, there are no always takers, $D_{i0}^P = 0$ for all i. There may however be never takers (n), $D_{i0}^P = D_{i1}^P = 0$.

Also by definition, there are no defiers. Instead, defiers (d) may exist with respect to another variable, D_i^A, which is an investment made in the absence of the pandemic. This would be captured by the question "Was there any investment that you had planned but were prevented from making by the pandemic?", which unfortunately we did not ask. Firms responding affirmatively to this hypothetical questions have $D_{i1}^A = 0$ and $D_{i0}^A = 1$, and we call them defiers. Firms responding in the negative to the question are never takers, $D_{i1}^A = D_{i0}^A = 0$. Again by definition, there are no always takers (the definition excludes investments made despite the pandemic, 'during not due to'). Thus, there are four groups of firms as follows.

- Compliers, defiers (cd): $(D_{i1}^P, D_{i0}^A) = (1, 1)$
- Compliers, never takers (cn): $(D_{i1}^P, D_{i0}^A) = (1, 0)$
- Never takers, defiers (nd): $(D_{i1}^P, D_{i0}^A) = (0, 1)$
- Never takers, never takers (nn): $(D_{i1}^P, D_{i0}^A) = (0, 0)$

Recall that $D_{i0}^P = 0$ for all i and $D_{i1}^A = 0$ for all i by definition, so these terms need not be listed.

We make the following *assumptions*:

$$\mathrm{E}[\tau_i|nn] \leq 0, \qquad \mathrm{E}[\tau_i|nd] \leq 0. \tag{C.1}$$

These assumptions imply that for the pandemic to causally increase a firm's frontier technology share, the firm must make a 'due to' investment, and that abandoning an investment due to the pandemic means that the frontier technology share increased by less than it would have in the absence of the pandemic. The assumptions are not entirely trivial. For instance, frontier technology shares could change as a result of differential depreciation. We assume that such an effect would be the same with or without the pandemic. However, note also that the assumptions are general when it comes to non-frontier technologies. For instance, non-complying firms may in fact be induced by the pandemic to invest more in non-frontier technologies, which is accounted for by the weak inequality in equation (C.1).

Letting π indicate probabilities, we therefore have

$$\begin{aligned}\underbrace{\tau}_{\text{ATE}} &= \pi(nn)\mathrm{E}[\tau_i|nn] + \pi(nd)\mathrm{E}[\tau_i|nd] + \pi(cn)\mathrm{E}[\tau_i|cn] + \pi(cd)\mathrm{E}[\tau_i|cd] \\ &= \pi(nn)\mathrm{E}[\tau_i|nn] + \pi(nd)\mathrm{E}[\tau_i|nd] + \pi(c)\mathrm{E}[\tau_i|c] \\ &\leq \pi(c) \times \underbrace{\mathrm{E}[\tau_i|c]}_{\text{ATT}}.\end{aligned}$$

Here, we define the average treatment effect on the treated (ATT) as the treatment effect among the compliers (which may include some, but not necessarily all, defiers). In words, the product of ATT and complier share is an upper bound on the average treatment effect of the pandemic.

But how can we estimate the ATT from data, given that we do not observe Y_{i0} for any firm? In particular, what can we learn from comparing firms that did invest 'due to' the pandemic to those that did not? As usual,

$$\begin{aligned}\mathrm{E}[Y_i|D_{i1}^P = 1] - \mathrm{E}[Y_i|D_{i1}^P = 0] &= \underbrace{\mathrm{E}[Y_{i1}|D_{i1}^P = 1] - \mathrm{E}[Y_{i0}|D_{i1}^P = 1]}_{\text{ATT}} \\ &\quad + \underbrace{\mathrm{E}[Y_{i0}|D_{i1}^P = 1] - \mathrm{E}[Y_{i0}|D_{i1}^P = 0]}_{\text{selection bias}} \\ &= \mathrm{E}[\tau_i|c] + B,\end{aligned}$$

where B is the selection bias. It is plausible—and we present some evidence as well—that $B \geq 0$. Therefore,

$$\pi(c)\left\{\mathrm{E}[Y_i|D_{i1}^P = 1] - \mathrm{E}[Y_i|D_{i1}^P = 0]\right\} = \pi(c)\left\{\mathrm{E}[\tau_i|c] + B\right\} \geq \pi(c)\mathrm{E}[\tau_i|c] \geq \tau.$$

In words, the observed difference in the change of the frontier technology share between 'due to' investors and those who did not make a 'due to' investment, multiplied by the share of 'due to' investors, is an upper bound for the effect of the pandemic on frontier technology adoption. If the difference is regression-adjusted, then the statement still holds provided that selection bias remains non-negative. Control variables may include firm characteristics such as size and sector, but also whether the firm made a frontier technology investment before the pandemic, or during but not because of it.

D Firm-level exposure and investment patterns

Here we explore whether differences in firm-level exposure to the pandemic predict firms' investment behavior. Our firm-level measures of Covid-19 exposure, elicited by the survey, include the number of weeks with forced closures, as well as indicators for: supply chain problems, declining product demand, declining revenues, having applied for government support, and experiencing severe uncertainty. We further consider industry-level revenue growth and local Covid-19 hospitalization rates. In addition, we explore the role of remote work potential (RWP) as measured by firms' pre-pandemic task mix. See Section 2 for details on these variables. We proceed by regressing frontier investment choices—in terms of timing and reason, as well as the change in the frontier technology share—on the mentioned variables, as well as the usual controls. We additionally control for the share of workers in remote work prior to the pandemic as high-RWP firms likely made greater use of remote work even before the pandemic. We also control for industry-level revenue growth prior to the pandemic.

Table A10 shows the results for office equipment. Few of the variables robustly predict having made a due-to investment (column (1)). Firms who applied for government support appear less likely to have invested due to the pandemic, and there is some weak evidence that firms experiencing severe uncertainty, and those seeing faster revenue growth in their industry, were more likely to invest due to the pandemic. Having applied for government support also predicts lower increases in frontier technology shares (columns (4)-(6)). Firms with greater remote work potential saw faster increases in frontier technology shares 2016–2021 (columns (4) and (5)), but this is likely because of investments made before the pandemic (column (2)), and these firms also had more ambitious plans in 2016 (column (7)). We obtain similar results when we weight by employment (Table A11). For production equipment, none of the variables appear to be predictive of technology adoption (Table A12).

Overall, we find no clear evidence that firm-level exposure to the pandemic drove frontier technology adoption. There are several possible reasons for this. Greater exposure may both present a greater need to adjust and re-organize on one hand, but on the other hand a lack of resources—managerial, financial, staffing—may prevent investments from materializing. Another possibility is that firm-level variation in exposure is rather small relative to the size of the aggregate shock, and therefore not a primary driving force.

Download ZEW Discussion Papers:

https://www.zew.de/en/publications/zew-discussion-papers

or see:

https://www.ssrn.com/link/ZEW-Ctr-Euro-Econ-Research.html
https://ideas.repec.org/s/zbw/zewdip.html

//
IMPRINT

ZEW – Leibniz-Zentrum für Europäische Wirtschaftsforschung GmbH Mannheim

ZEW – Leibniz Centre for European Economic Research

L 7,1 · 68161 Mannheim · Germany
Phone +49 621 1235-01
info@zew.de · zew.de