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DISCUSSION PAPER SERIES

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ABSTRACT

Firm-Level Technology Adoption in Times of Crisis*

We investigate the diffusion of frontier technologies across German firms before and during the Covid-19 crisis. Our analysis tracks the nature, timing, and pandemic-related motivations behind technology investments, using tailor-made longitudinal survey data linked to administrative worker--firm records. Technologies adopted after the onset of the pandemic increasingly facilitated remote work and mitigated the negative employment effects of the crisis. Overall, however, investments in frontier technologies declined sharply, equivalent to a loss of 1.4 years of pre-pandemic investment activity. This procyclical adoption pattern is particularly striking since the pandemic created clear incentives to experiment with new technologies. Our findings highlight how short-run fluctuations may influence medium-run economic growth through their impact on technology diffusion.

JEL Classification: O33, E22, E32, J23

Keywords: frontier technology investments, firm-level survey data, cyclicality of technology adoption, COVID-19

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1 Introduction

The past ten years have seen a surge in digital and data-driven innovations. Their impact on productivity growth is not guaranteed but depends on the diffusion of technology across firms. However, the factors shaping this diffusion process remain insufficiently understood, particularly in the context of business cycle fluctuations.

In this paper, we examine how the Covid-19 pandemic—one of the major macroeconomic events of the 21st century—influenced firms' adoption of frontier technologies. The pandemic presents a compelling case study of technology diffusion under economic distress. While it triggered a severe downturn that may have curtailed investments, it also created unprecedented challenges that could have spurred the adoption of new innovations. Studying firms' adaptive responses during Covid-19 provides insights into the broader dynamics of technology diffusion in times of crisis and sheds light on the pandemic's long-term economic legacy.

In a representative survey, we asked German firms about their adoption of frontier technologies—defined as technologies developed since the late 2000s that are self-controlled and fully integrated into central IT systems.[1] We inquired whether firms had invested in frontier technologies between 2016 and 2022, when these investments took place, and, if they occurred after the onset of the pandemic, whether Covid-19 influenced the decision to invest. To examine the direction of technology adoption, we also asked about the specific applications of the installed technologies. To quantify adoption, firms reported the share of frontier technologies among all technologies they currently use and how this share has changed over the preceding years. Additionally, a subset of respondents had participated in our previous survey on technology adoption in 2016, allowing us to track changes in a panel of firms over time. Our survey data provide direct measures of the pandemic's impact on technology diffusion, rather than relying on coarser measures of firm-level pandemic exposure.

We obtain two key findings. First, the adoption of new technologies declined sharply during the Covid-19 pandemic. Annualized investment rates fell to just half of pre-pandemic levels, and only a small share of firms reported making technology investments specifically because of the pandemic (see Figure 1). We estimate that, absent the pandemic, the share of frontier technologies would have grown 50% more between 2016 and 2022 than it actually did.[2]

[1] See Section 2 for a detailed definition of frontier technologies. While our survey technically targeted establishments, we use the term 'firm' for brevity.

[2] Put differently, we observe a decline in technology growth 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 of technology adoption in the medium run: Firms that did invest during the pandemic do not have more ambitious plans for the coming five years than other firms.

Second, the pandemic influenced not just the pace but also the direction of technology adoption. We document a marked shift in the types of technologies firms prioritized, with significantly higher investment in remote work technologies as well as communication and collaboration tools compared to technologies for management, product design, or process automation (see Figure 2).[3] We find some evidence that this shift helped firms to adapt to changed circumstances: Pandemic-induced investments are associated with greater use of remote work, a lower reliance on subsidized short-time work, and overall a smaller contraction of employment.

Five distinct features make our survey a uniquely-suited data source for assessing the impact of the pandemic on technology adoption. First, our phone interviews elicit frontier technology adoption using up-to-date concepts and examples, unlike administrative records or company accounts which employ older and broader categories (such as 'hardware' and 'software'). Second, by collecting detailed information on the timing of investments and firms' pandemic-related motivations, we can distinguish between investments induced by the pandemic and those that merely coincided with it. Third, our open-ended questions provide precise insights into the applications of newly adopted technologies. When combined with firms' stated motivations, this allows us to document not only the extent but also the direction of technology adoption. Fourth, by asking firms about their future plans for adopting frontier technologies, we extend our analysis beyond short-term impacts to assess potential medium-term effects of the pandemic. Fifth, for a subset of firms, we have pre-pandemic investment plans that serve as a counterfactual baseline, allowing us to compare actual investments with what would have occurred in the absence of the pandemic. We believe that these features, appropriately adapted, would benefit future surveys of technology adoption taking place under adverse aggregate conditions, thereby further improving our understanding of technology adoption in times of crisis.

Our paper contributes to four strands of the literature: the effects of crises on technology investments, drivers of technology diffusion, business surveys, and the impact of Covid-19 on technology adoption.

First, using detailed firm-level evidence, we add to the understanding of technology investments during crises and recessions, which has important implications for the welfare effects of the business cycle (Cerra et al., 2023). Prior research shows that investments in research and development (R&D) tend to be less cyclical—or even countercyclical—compared to aggregate investment or physical capital investment (Aghion et al., 2012; Bloom, 2007). At the same time, recent research in labor economics suggests that technological change often accelerates its impact on workers and jobs during downturns (Hershbein and Kahn, 2018; Jaimovich and Siu, 2020). This raises the question of whether

[3] Among surveyed firms, there was virtually no pandemic-driven investment in advanced production technologies. Section 2 discusses the distinction between office and production technologies.

the adoption of new technologies, which partly overlaps with R&D but primarily follows it through diffusion,[4] exhibits a similar pattern.

Compared to R&D, evidence on the cyclicality of frontier technology adoption remains scarce. Our findings suggest that adoption behaves more like aggregate investment, slowing down during crises rather than remaining stable or increasing. This slowdown represents an under-appreciated adverse effect of economic downturns. We also document a shift in the types of technologies adopted, with firms prioritizing crisis-response technologies that are less transformative for long-term technological progress. These findings align with theories of directed technical change (Acemoglu et al., 2012; Newell et al., 1999) but also with option value theories of investment, which suggest that heightened uncertainty leads firms to delay irreversible investments (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 classic research on diffusion patterns (Acemoglu and Restrepo, 2022; Bloom and Van Reenen, 2007; Griliches, 1957).[6] We advance this literature by analyzing how an aggregate shock—the Covid-19 pandemic—affected the adoption of frontier technologies.

Third, firm-level surveys have become an increasingly valuable tool in economic research. For example, Altig et al. (2020) and Bloom et al. (2025) have used them to analyze the macroeconomic impact of Covid-19, while most surveys on technology adoption focus on micro-level determinants.[7] The detailed information that we collect is novel and a strength for studying the impact of Covid-19 on technology adoption, also compared to existing studies or the use of external exposure measures. Our information on the timing, reasons, and applications of investments are particularly valuable for policymakers, given that such granular information is rarely available for specific crises.

Finally, our paper contributes to the active debate on whether Covid-19 accelerated technological change. Several crisis-driven innovations[8] as well as the rise of remote work (Barrero et al., 2023) and digital interactions (Avalos et al., 2023) have been taken to indicate an acceleration of technological progress (LaBerge et al., 2020; Valero et al., 2021).

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

[5] A Covid-specific factor contributing to the slowdown may be that pandemic-related disruptions and lockdowns could have made it harder to implement new technologies. However, in our data, we find no correlation between firms' Covid-19 exposure and their technology investment behavior. For a discussion of the specificity of Covid-19 and the merits of case studies, see Sections 3 and 6 respectively.

[6] Part of our analysis examines the link between frontier technology adoption and labor demand, similar to Acemoglu et al. (2020); Bessen et al. (2020); Gaggl and Wright (2017); Koch et al. (2021).

[7] Unlike macro-level shocks, these determinants are often hard to distinguish from firm selection (see for instance Acemoglu et al., 2023).

[8] Examples include mRNA vaccines, contact tracking, air purification, and mass online learning; see also `https://www.covidinnovations.com/`.

Two studies specifically examine firm-level technology adoption during the pandemic: Barth et al. (2022) find that Norwegian firms adopted new technologies in response to Covid-19, while Gathmann et al. (2024) report that half of German firms invested in digital technologies, interpreting this as a "pandemic push."

Our findings provide a more nuanced perspective. By incorporating pre-trends, constructing counterfactuals, and distinguishing between different types of investments,[9] we show that while Covid-19 spurred remote work investments, these were often less impactful and did not accelerate overall frontier technology adoption. Instead of a broad-based push, our results suggest that the pandemic primarily redirected technological progress toward supporting remote work (Bloom et al., 2021).

The paper proceeds as follows. Section 2 introduces our novel firm-level dataset and provides baseline descriptive statistics. Section 3 develops two hypotheses on the impact of the pandemic on technology adoption: one suggesting a crisis-induced push, the other a shift in adoption patterns. The section also explains how our survey data allow us to distinguish between these hypotheses. Section 4 presents the 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

[9] Gathmann et al. (2024) include all digital investments, while we focus specifically on frontier technologies, aligning with recent studies on technology diffusion.

our results representative of the population of German firms.[10] 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).

Timing and period lengths. The median date for the BIZA II survey was April 1, 2022, with the vast majority of interviews occurring in the calendar year 2022 (see Figure B1 for the distribution of interview dates). Therefore, we refer to 2022 as the year when BIZA II took place. The earlier BIZA I survey was conducted in 2016, and when respondents in BIZA II were asked retrospective questions on investments, they primarily referred to numbers from 2016 unless their firms were established later. As a result, we refer to 2016–2022 as our analysis period throughout the paper.[11]

Within this time frame, we distinguish between periods before and during the Covid-19 pandemic. The pandemic period for each firm is defined as the time from its respective survey date minus February 2020, when the pandemic officially reached Europe, averaging 2.11 years in our data. The pre-pandemic period is determined as February 2020 minus the midpoint of the reference year, which is typically 2016 (i.e., 2016.5) as explained above. Since some firms have later reference years, the average pre-pandemic period across all respondents is 3.54 years. Overall, 63% of our analysis period falls before the pandemic, while 37% occurs during it. These relative period lengths are used, for example, in Figure 1 or Table 5 to annualize investment rates and construct counterfactual technology changes, respectively. None of our results substantively depend on the exact calculation or length of the pandemic versus pre-pandemic periods.

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*

[10] 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.

[11] Questions about frontier technology *shares*—as opposed to specific investments—specified time frames as "five years ago" and "in five years' time". To ease exposition, we consistently refer to 2016 as the beginning of our period, both when discussing investments and changes in technology shares. See Figure A1 for the evolution of office and production frontier technology shares from 2011 to 2022.

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).[12] 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 distribution 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 since 2016, 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 dif-

[12] 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.

ferent 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).[13] 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 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.[14] This structure of our questionnaire results in a categorization

[13] 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.

[14] 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 have verified the robustness of our results to these potentially unobserved investments. Results are available upon request.

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 Bureau van Dijk's ORBIS-AMADEUS database, as used for instance by Gopinath et al. (2017).

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). Of the original BIZA I firms, 465 participated 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 five years later. 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 the BIZA II period. 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 2022.[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 2016–2022. 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 firm-level employment growth, 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 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. 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

[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.

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 introduce our hypotheses about the effects of the Covid-19 pandemic on frontier technology adoption and explain how we use our survey data to test them.

3.1 Hypotheses about the pandemic and technological progress

Two main hypotheses guide our analysis of how the pandemic affected frontier technology adoption: the crisis push hypothesis, which posits that the pandemic accelerated adoption, and the crisis shift hypothesis, which suggests that the pandemic altered the direction of adoption toward remote work technologies. These hypotheses are not mutually exclusive.

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). Since frontier technology adoption partly overlaps with R&D and partly follows it through diffusion, the cyclicality of R&D may offer relevant lessons. Unlike overall investment, which tends to be strongly pro-cyclical, R&D appears acyclical or even countercyclical (Aghion et al., 2012; Bloom, 2007). Theoretical explanations include the opportunity cost channel (Aghion and Saint-Paul, 1998; Francois and Lloyd-Ellis, 2003), which suggests that downturns reduce the cost of reallocating resources toward innovation, and a "caution effect" (Bloom, 2007). However, financial constraints (Aghion et al., 2010; Campello et al., 2010), heightened uncertainty (Bloom et al., 2007), and dynamic spillovers (Barlevy, 2007) could instead make R&D and frontier technology adoption pro-cyclical.

During the pandemic, credit constraints may have been less binding than in past recessions due to extensive government support,[16] while the urgency to implement new

[16]While credit constraints significantly curtailed investment during the global financial crisis (Campello et al., 2010), generous government liquidity provisions during Covid-19 mitigated such effects (German Ministry of Finance, 2020; German Ministry of Economic Affairs, 2022).

technologies may have been greater. At the same time, pandemic-related disruptions and lockdowns could have hindered technology adoption, though our data show no correlation between firms' Covid-19 exposure and investment behavior (see Appendix C). Moreover, substantial evidence suggests that the pandemic was a severe uncertainty shock (Altig et al., 2020; Morikawa, 2021), which may have influenced firms' investment decisions.

Under the crisis push hypothesis we expect three key patterns: First, a substantial share of firms should report that their primary technology investments were driven by the pandemic. Second, investments made due to the pandemic should be associated with significant 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 pandemic-induced investments may raise firms' planned long-term technology adoption, too.

Crisis-induced shift in technology adoption (crisis shift). This hypothesis suggests that the pandemic altered the direction of technology investments, particularly by pushing firms to adopt remote work technologies in order to sustain 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). As a result, firms prioritized technologies that facilitated remote work and virtual collaboration. Evidence of this shift extends beyond firm-level adoption—Bloom et al. (2021) document a surge in patents for remote work technologies during the pandemic. More broadly, this hypothesis aligns with theories of directed technological change, where external conditions shape the trajectory of innovation and technological adoption (Acemoglu, 2002; Acemoglu et al., 2012).

However, under the crisis shift hypothesis, technology adoption may have been relatively marginal, representing secondary rather than transformative investments. Empirical research suggests that while external shocks can redirect technological change, they do not necessarily accelerate its overall pace (Newell et al., 1999).[17] Since many remote work tools could be implemented—or later reversed—with relatively small cost, firms may have prioritized them as short-term solutions rather than as part of broader technology adoption strategies.

We may thus expect three key adjustments among firms under the crisis shift hypothesis: First, investments should exhibit a marked redirection toward technology applications that enable remote work. Second, unlike the crisis push hypothesis, these investments will more often be secondary rather than what firms consider their main investment during

[17] Barrero et al. (2021) argue that large-scale experimentation during Covid-19 cemented remote work as a lasting practice. Pre-pandemic evidence also supports this notion—Bloom et al. (2015) found that firms experimenting with remote work tended to retain it. While remote work should have led to substantial welfare gains (for instance, Le Barbanchon et al., 2021), such technologies may have matured, reducing the need for extensive future investments.

the period 2016–2022. If so, their impact on overall firm-level technology adoption and long-term follow-up investments will be limited. Third, firms that adopted frontier technologies during the crisis should exhibit higher rates of remote work, which in turn should help stabilize output and employment, thus reducing reliance on short-time work schemes.

3.2 Empirical strategy

The hypotheses outlined above generate clear predictions about firms' adoption of frontier technologies during the pandemic. Testing these predictions requires rich data and well-defined counterfactuals.

Our survey data allow us to track frontier technology adoption during the pandemic along several margins: whether firms introduced new technologies, how much their frontier technology shares increased, and what applications these technologies served. Importantly, firms also reported the pandemic-related motivations behind their investments.

We assess the **crisis push hypothesis** using three main empirical tests: First, we compare investment rates during the pandemic to the preceding period and estimate a counterfactual rate of frontier technology growth that would have occurred without the pandemic. Second, we use investment plans from our 2016 survey as an alternative counterfactual, allowing us to measure deviations from pre-pandemic expectations. Third, using regression analysis we compare the effect of pandemic-induced investments on firms' technology shares with that of other investments, controlling for sector, location, workforce composition, and baseline productivity to account for potential confounding factors.

To test the **crisis shift hypothesis**, we leverage detailed data on the applications, timing, and motivations of newly adopted frontier technologies, as well as their impact on technology shares. For instance, we compare the prevalence of remote work technologies among pandemic-induced investments to their prevalence in pre-pandemic investments, shedding light on whether the pandemic redirected firms' technology adoption priorities.

A potential alternative approach is to leverage firms' differential exposure to Covid-19 using observable variables such as pre-pandemic work arrangements, regional infection rates, and sectoral demand shifts. However, none of these variables robustly predict changes in investment patterns (see Appendix C). This suggests that the pandemic primarily acted as an aggregate economic shock, with general uncertainty and demand declines being the key factors influencing technology adoption decisions.

Nevertheless, there is cross-sectional variation in our survey responses—in particular, the incidence of investments due to the pandemic—that informs the effect of the pandemic on aggregate technology adoption. In Appendix D, we model heterogeneity in the pandemic's effects using the standard potential outcome framework, and present the conditions under which our regression analysis set-identifies the average treatment effect of the pandemic on firms' technology adoption.

4 Evidence on the crisis push hypothesis

We begin by examining the crisis push hypothesis—whether the Covid-19 crisis accelerated the adoption of frontier technologies. Section 4.1 documents the timing of investments, distinguishing between those made before, during, and explicitly due to the pandemic. It also breaks down the overall change in frontier technology shares based on these investment categories. Building on these descriptive findings, Section 4.2 employs regression analysis to estimate the effects of each investment type while controlling for potential confounding factors, including firms' pre-pandemic plans. Finally, Section 4.3 quantifies the pandemic's overall impact on frontier technology adoption.

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

Figure 1 illustrates the annualized rates of frontier technology investment before and during the Covid-19 pandemic, adjusted for differences in period lengths, as outlined in Section 2.1. Prior to the pandemic, over six percent of firms per year invested in frontier office technology. However, this investment rate dropped significantly to 3.6 percent during the pandemic, a decline of nearly 50 percent in relative terms. The drop was even more pronounced for production technology, where investment rates fell from three percent to just 0.5 percent. Notably, among the office technology investments made during the pandemic, only half were explicitly attributed to the crisis. Pandemic-driven investments in production technology were in fact negligible.

The evidence presented in Figure 1 appears to contradict the crisis push hypothesis, instead indicating a sharp decline in frontier technology adoption. However, we note two caveats: First, for interpretational clarity the figure is only based on the main frontier technology investment that each firm made during 2016–2022. Second, the figure speaks to the extensive margin only—whether firms invested—without accounting for the intensive margin, meaning the extent to which investments increased firms' overall frontier technology shares.

Table 3 addresses these limitations by incorporating both primary and secondary investments as well as the changes of frontier technology shares. Column (1) shows the percentage of firms engaged in various investment combinations. Panel A reveals that the share of main office technology investments made before the pandemic was 22.3%, while those occurring during the pandemic but not explicitly due to it were 3.9%, and those made specifically due to the pandemic accounted for only 3.7%.[18] However, there is a substantial incidence of secondary investments, especially pandemic-induced ones.

[18]These are the numbers which, annualized, are shown in Figure 1. 70.1% of firms did not make any investment in office frontier technologies at any point in time between 2016 and 2022.

For instance, 5.0% of firms made their main office investment before the pandemic and a secondary investment due to the pandemic. When accounting for these secondary investments, the overall share of firms reporting pandemic-driven investments rises to 10.1%.

Columns (2) and (3) of Table 3 help assess whether due-to investments had a meaningful impact on frontier technology shares. On average, the share of office technology classified as frontier increased by 3 percentage points between 2016 and 2022. The contributions of firms with main investments due to the pandemic (15.0%) and during the pandemic but not explicitly because of it (10.3%) are relatively small compared to the 80.0% contribution of firms that made their main investments before the pandemic. When secondary investments are included, firms with any pandemic-driven investments account for 38.1% of the overall increase in frontier office technology shares (15.0% from main investments plus 23.1% from secondary due-to investments). However, this overall figure does not account for whether firms had already invested before the pandemic, potentially overstating the impact of pandemic-driven investments. Moreover, firms that invested at different times or for different reasons vary in their baseline characteristics, which may have influenced their technology adoption trends even in the absence of the pandemic.[19] We address these concerns through regression analysis in the next section.

The evidence against the crisis push hypothesis is already very clear for production equipment (panel B). A full 87.8% of firms reported no frontier investments in this category during the study period, while 11.6% invested before the pandemic, 3.9% during but not due to it, and virtually none attributed their investments to the pandemic. As a result, the modest overall increase of just 0.6 percentage points in the frontier share of production technology is almost entirely driven by investments made before or independently of the pandemic.

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

We now use regression analysis to estimate the association between changes in frontier technology shares and investing due to the pandemic, holding constant whether the firm invested before the pandemic or during but not due to, as well as controlling for a rich set of covariates. The analysis gets us closer to a causal interpretation. While we lack a clean natural experiment, we argue in Appendix D that the coefficient on the indicator for due-to investments is an upper bound for the average treatment effect on the treated—firms whose investments were affected by the pandemic—which in turn can be used to bound the average treatment effect of the pandemic.

[19] Frontier investors compared to non-investors are larger, more likely to operate in knowledge-intensive sectors, have a more educated workforce and greater 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 A1 for details.

We regress the change in the frontier technology share of firm i over 2016–2022 on indicators characterizing the firm's investment activity. In particular, we estimate the model

$$\begin{aligned}\Delta_{2016,2022}\ \text{Frontier share}_i \\ = \lambda_1 \text{Before}_i + \lambda_2 \text{During, not due}_i + \lambda_3 \text{Due to}_i + \beta X_i + \varepsilon_i,\end{aligned} \tag{1}$$

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.

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.[20] 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. 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 due-to investors would have adopted frontier technology at a higher rate even in the absence of the pandemic.

[20] Results are largely unchanged when weighting the regressions by baseline employment, see Table A4. We report results on production equipment in Table A5.

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.[21] 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 due-to investors are a positive selection of firms.

Main investments due to the pandemic turn out to be comparable to other main investments in raising the frontier technology share, as seen in panel C of Table 4. 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. Recall however that main investments due to the pandemic are rare.

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 2016–2022 and planned investments during the next five years.

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. Main 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.

[21] The estimation equation underlying these results is

$$\Delta_{2016,2022} \text{ Frontier share}_i = \delta_1 \text{Main}_i + \delta_2 \text{Secondary}_i + \pi X_i + \eta_i.$$

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.

4.3 Quantifying the overall effect of the pandemic

In the previous section, we reported a small and likely upward-biased estimate of the effect of pandemic-driven investments on frontier technology shares. To gauge the overall effect of the pandemic, we also need to take account of investments that were lost due to the pandemic.[22] 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 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 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 2016–2022) 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 as well as the likely positive selection of due-to investors 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 discussed in Section 2.1). 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

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

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 during normal times.[23] The slow down, in terms of percentages and years of investment activity lost, is quite similar for production technology (compare Table A6).

5 Evidence on the crisis shift hypothesis

We now turn to the crisis shift hypothesis, which posits that the pandemic altered the direction of technology adoption, and examine the type of technologies firms invested in due to the pandemic. We use the responses to our open-ended survey question asking which specific frontier technologies firms invested in, combined with information on the timing and stated motivation for the investment.

5.1 Classifying frontier technologies by application

To systematically classify frontier technology investments by application, we employed a supervised machine learning approach. We first used ChatGPT to generate descriptions for each technology mentioned in the survey. Next, for both office and production equipment, we defined a set of categories to group these technologies. In the case of office equipment, these include 'communication and collaboration tools', 'cloud computing', and 'basic IT infrastructure', among others.

To ensure accurate classification, we manually categorized a subset of the reported technologies to create a training dataset. We then trained a Neural Network Classifier (NNC) to categorize the remaining technologies into the groups based on the descriptions provided by ChatGPT. This approach allowed us to classify a total of 2,526 office technologies and 457 production technologies. For a more detailed description of the classification process and an evaluation of its accuracy, see Appendix B.4.

[23] 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.

5.2 Shifts between technology applications

Our data are now at the level of individual technology investments, so that there can be multiple observations per firm. To examine how the pandemic influenced the composition of frontier technology investments, we compare the distribution of investment applications before, during (but not due to), and explicitly due to the pandemic. Figure 2 illustrates these shifts, showing the percentage share of investments across different technology categories for each period. To highlight changes in remote work-related technologies, we color-code categories facilitating remote work in shades of red, while all other technologies appear in shades of blue.

Figure 2 shows that before the pandemic investments in remote work technologies—categorized as 'IT infrastructure for remote work' and 'communication and collaboration tools'—accounted for little more than 10% of all office technology investments. However, this share increased significantly after the onset of the pandemic. Among investments made during the pandemic but not because of it, remote work-related technologies already accounted for over 20%. The shift is even more dramatic for investments explicitly motivated by the pandemic: More than half of these investments fell into the IT infrastructure for remote work or communication and collaboration tools categories.

Interestingly, some technology categories that might have seemed more relevant during the pandemic did not experience similar increases. Notably, the shares of 'cloud computing infrastructure' and 'E-commerce and customer interaction' investments declined slightly compared to pre-pandemic levels. Meanwhile, technologies related to 'management, product design, and planning' as well as 'data analytics and visualization' were almost entirely absent among due-to investments, despite jointly accounting for more than 15% of both pre-pandemic and during-but-not-due-to investments.

Overall, we observe a clear pandemic-driven shift in the types of technologies firms prioritized, with a strong redirection toward technologies that support remote work. Potentially more complex or transformational investments, such as those in cloud computing and E-commerce, did not experience a similar surge. This finding aligns with our earlier result that the pandemic did not broadly accelerate frontier technology adoption. Instead, many pandemic-driven remote work investments were secondary, suggesting a focus on short-term operational adjustments rather than long-term technological transformation—a pattern that we further examine in the next section.[24]

[24] Note that these shifts are not merely driven by differences between firms that did and did not make due-to investments. When comparing pre-pandemic and due-to investments only among firms that made pandemic-driven investments, we observe the same shift toward remote work technologies. See Figure A2. Similar analyses cannot be conducted for production technologies, as pandemic-driven investments in this category were negligible.

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 mandates, 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 complicated by the widespread use of state-financed short-time work schemes (STW; see Appendix B.3 for details). These programs allowed firms to reduce working hours without formally reducing headcount, meaning that the number of employees may have remained stable even as actual labor input declined. To account for this, we analyze not only overall employment, but also the share of 'non-regular' employment—primarily marginal workers who are ineligible for STW—as well as the share of employees actually placed on short-time work.

We estimate the following firm-level model:

$$\begin{aligned} \Delta_{2019,2022}\ &\text{Employment outcome}_i \\ &= \kappa_1 \text{Before}_i + \kappa_2 \text{During, not due}_i + \kappa_3 \text{Due to}_i + \gamma X_i + u_i, \end{aligned} \tag{2}$$

where the dependent variable captures the change in one of four employment outcomes between 2019 (pre-pandemic) and 2022. These include: the share of employees working from home (WfH), as reported in our survey; overall log employment; the share of non-regular employment; and the share of workers on short-time work (STW).[25]

The coefficient κ_3 captures the association between having invested in digital technologies due to the pandemic and each employment outcome. To mitigate potential selection bias, we control not only for a comprehensive set of firm characteristics, X_i, as in previous specifications, but also for measures of the firm's exposure to the Covid-19 shock.

Table 6 presents the results from estimating equation (2). Column (1) reveals a strong positive association between pandemic-induced investments and the increase in the share of employees working from home. The estimated effect of 21pp is substantial, particularly in light of the average WfH increase of 15pp across firms. In contrast, neither pre-pandemic investments nor those made during the pandemic for other reasons show any

[25]The WfH measure is based on survey responses indicating the share of employees working from home at the time of the interview and prior to the pandemic. All other variables are drawn from administrative data. For short-time work, we use values from 2021, when the program was most widely utilized (mean STW share: 10.9%). We also use the level rather than the change, as STW in other years was minimal (e.g., mean share in 2022: 0.9%).

significant relationship with WfH adoption. The result is also robust to controlling for the pandemic exposure variables in column (2). This evidence aligns with the crisis shift hypothesis, suggesting that technology investments explicitly motivated by the pandemic were indeed targeted at enabling remote work. Naturally, we acknowledge that residual selection effects cannot be fully excluded.

Columns (3) to (6) of Table 6 report results for overall employment growth and growth in non-regular employment. While the coefficients on pandemic-induced investments are imprecisely estimated, the positive point estimates do not contradict the idea that such investments may have cushioned employment losses. The evidence is somewhat stronger in the case of short-time work. Columns (7) and (8) show that firms investing in response to the pandemic displayed a significantly smaller STW usage—by approximately 5 to 7pp—compared to the economy-wide average of 11pp.[26]

Finally, we have also investigated the associations between Covid-induced investments by application and employment outcomes. Indeed, 'IT infrastructure for remote work' as well as 'communication and collaboration tools'—both of which saw widespread adoption during the pandemic—are strongly positively related to the WfH share (see Table A7). These associations weaken somewhat when including investments that were not made due to the pandemic.[27] 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.[28] 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

[26]Columns (7) and (8) also show a positive and statistically significant association between STW and investments made during but not due to the pandemic. This may reflect an opportunity cost mechanism, as discussed in Section 3: firms facing reduced demand and benefitting from government-funded STW may have opted to suspend production and implement new technologies. However, as noted earlier, such firms represent a small share and are unlikely to drive aggregate trends in technology adoption.

[27]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).

[28]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.

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, our study has focused on the specific case of the Covid-19 crisis while also highlighting its broader business cycle implications.[29] We argue that, compared to other economic downturns, the pandemic provided relatively strong incentives for firms to experiment with new technologies. 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.

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[29]Related, Altig et al. (2020) and Bloom et al. (2025) use firm-level surveys to examine the effects of Covid-19 on economic uncertainty and productivity, respectively. Our findings complement their work by studying the pandemic's impact on technology adoption, which is an important channel and outcome related to uncertainty and productivity dynamics during the crisis.

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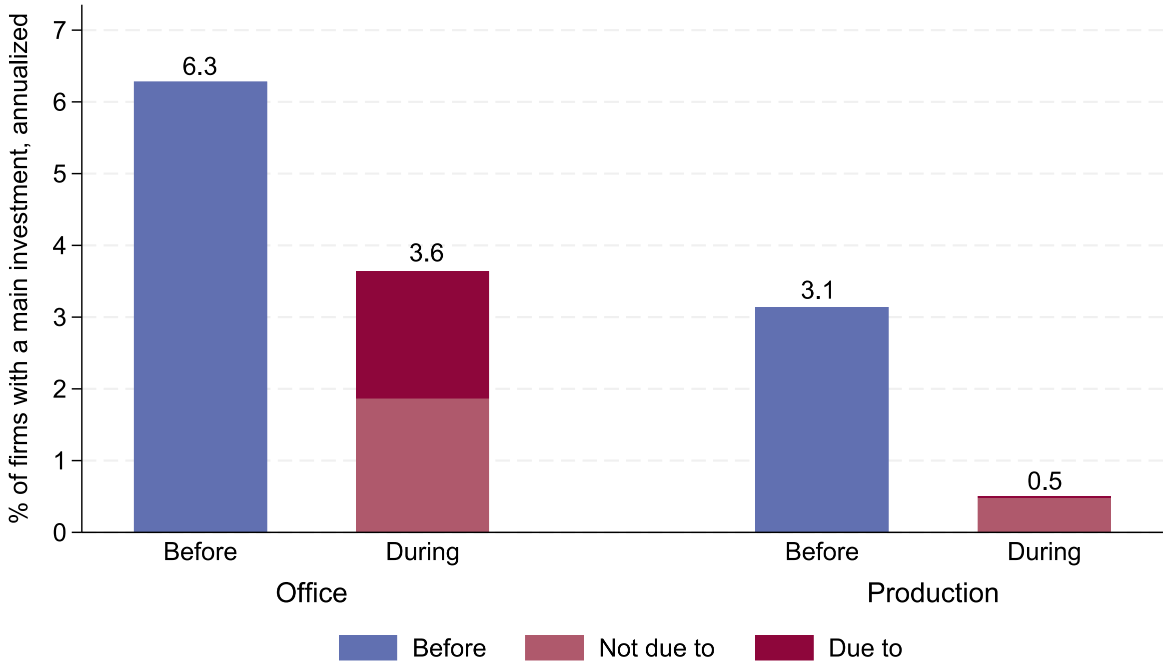
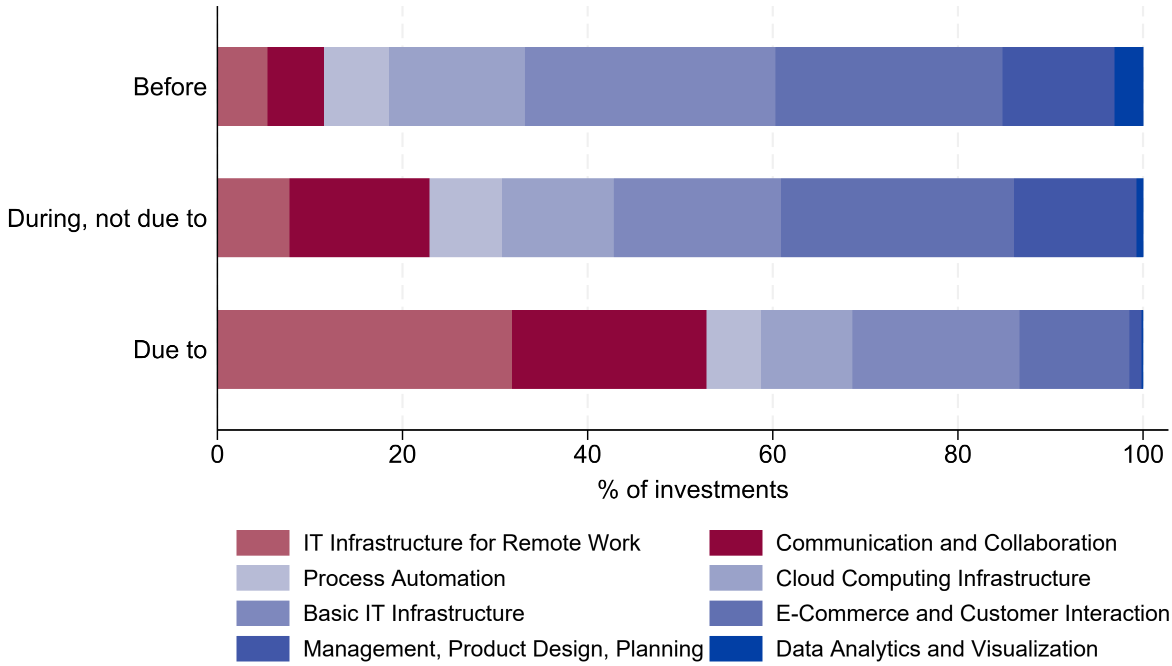
Figure 1: Annualized investment rates in frontier technology before and during Covid-19



Notes: The figure shows the rates of investment in office and production frontier technology before versus during the Covid-19 pandemic. Investments during the pandemic are further categorized based on whether they were made due to the pandemic. Only main investments are included. Annualized numbers from Table 3 given that the period before (during) the pandemic was on average approximately 3.54 (2.11) years long.

Figure 2: Investments in office equipment by application



Notes: The figure shows the distribution of technology applications among investments before the pandemic; during, not due to the pandemic; and due to the pandemic. Remote work technologies appear in shades of red while all other investments appear in shades of blue. Based on 2,526 unique main and secondary investments.

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 2022			Panel		
	All	*No missings*		*All*	*No missings*	
	Mean (1)	Mean (2)	SD (3)	Mean (4)	Mean (5)	SD (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 $\frac{1}{3}\sum_{t=2017}^{2019}\log(R_{i,t}/R_{i,t-1})$. Of the 2,268 firms used for columns (2) and (3), 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.

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				
	2016–22				2022–2027
	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),

$$\overline{\Delta_{2016,2022} \text{ Frontier technology share}_i} = \widehat{\lambda_1} \times \overline{\text{Before}_i} + \widehat{\lambda_2} \times \overline{\text{During, not due}_i} + \widehat{\lambda_3} \times \overline{\text{Due to}_i} + \widehat{\beta} \times \overline{X_i},$$

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

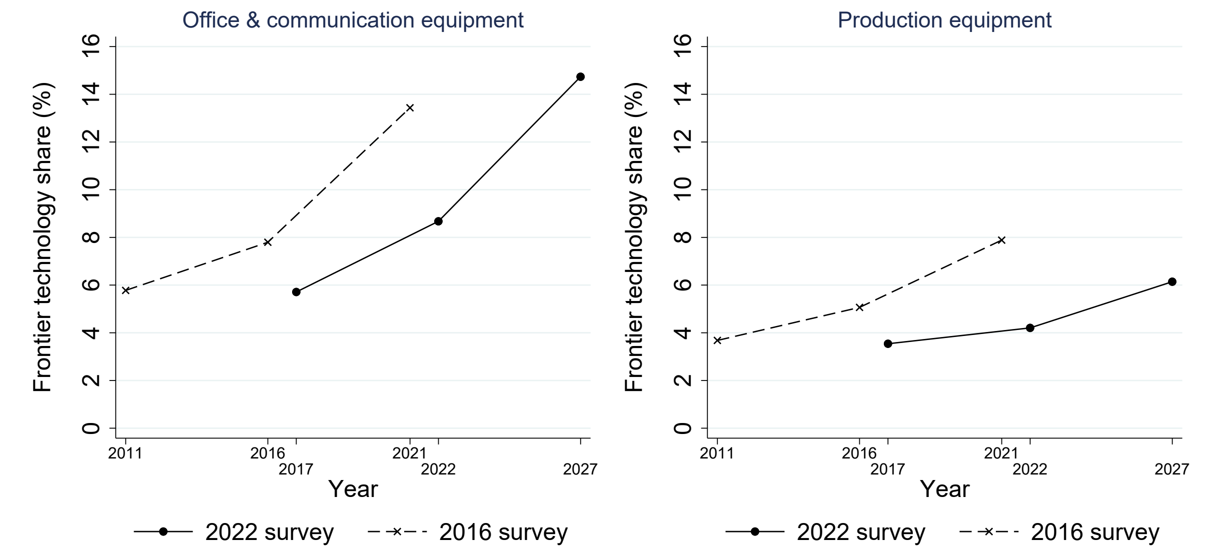
	Δ employees working from home in %		Δ log employment × 100		Δ share of employment not liable to social security in %		Employees in short-time work in 2021 in %	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Before	-2.21	-3.87	2.47	-0.55	2.90	2.70	-1.34	0.26
	(2.84)	(2.86)	(6.12)	(6.96)	(1.97)	(2.08)	(2.57)	(2.35)
During, not due to	2.07	2.83	-4.43	-1.92	0.95	0.45	17.1***	11.0***
	(3.39)	(3.05)	(9.01)	(9.07)	(2.12)	(2.24)	(5.75)	(4.13)
Due to	21.4***	20.5***	5.77	3.35	2.32	2.85	-6.67*	-4.78
	(4.60)	(4.44)	(6.07)	(6.12)	(2.07)	(2.07)	(3.92)	(3.00)
Observations	2,214	2,214	2,213	2,213	2,213	2,213	2,145	2,145
R-squared	0.32	0.38	0.14	0.16	0.14	0.15	0.24	0.39
Mean of dependent variable	15.0	15.0	-6.1	-6.1	-3.0	-3.0	10.9	10.9
Covid controls		✓		✓		✓		✓

Notes: The table reports results from regressing changes in employment indicators 2019–2022 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 A8. Regressions are weighted using sampling weights. Robust standard errors in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

Appendices for online publication

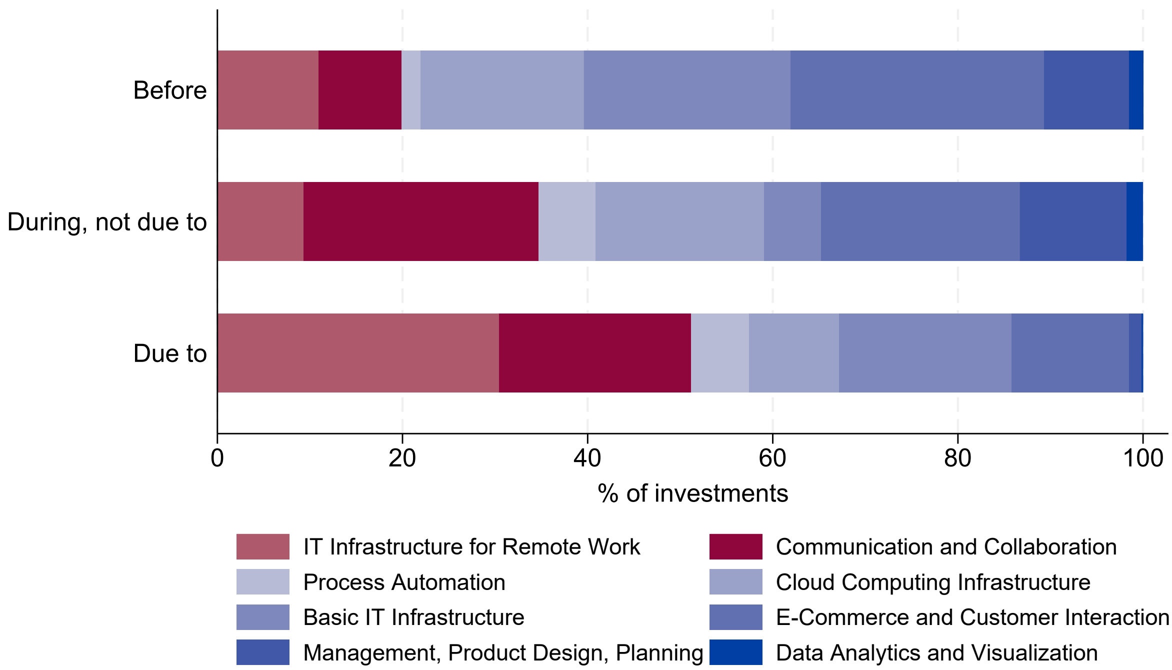
A Appendix figures and tables

Figure A1: Frontier technology shares over time



Notes: The figure displays the overall share of frontier work equipment over time. Interviews in BIZA II (2022 Survey) were mostly carried out in 2022 and respondents were asked about technology shares “five years ago” or “in five years time” (see footnote 11), so the data for 2017 and 2027 on the solid lines are based on respondents’ recollections and expectations. Interviews in BIZA I (2016 Survey) took place in 2016 and the points on the dashed lines result accordingly.

Figure A2: Investments in office & communication equipment by application—due-to investors only



Notes: The figure shows the distribution of technology applications among investments before the pandemic; during, not due to the pandemic; and due to the pandemic. Remote work technologies appear in shades of red while all other investments appear in shades of blue. The sample is restricted to firms that made an investment due to the pandemic, such that percentage shares are based on 1,154 unique main and secondary investments.

Table A1: 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	1%		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 A2: 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 A3: 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 A4: Changes in frontier technology shares by investment characteristics—office & communication equipment, weighted by employment

	Change in frontier technology share				
	2016–22				2022–27
	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 A5: Changes in frontier technology shares by investment characteristics—production equipment

	Change in frontier technology share				
	2016–22				2022–27
	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: 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),

$$\overline{\Delta_{2016,2022} \text{ Frontier technology share}_i} = \widehat{\lambda_1} \times \overline{\text{Before}_i} + \widehat{\lambda_2} \times \overline{\text{During, not due}_i} + \widehat{\lambda_3} \times \overline{\text{Due to}_i} + \widehat{\beta} \times \overline{X_i},$$

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 A7: 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***	10.0	7.69	3.43	4.21	1.49	2.46
	(5.92)	(5.91)	(11.5)	(12.3)	(2.21)	(2.68)	(3.92)	(3.29)
Basic IT infrastructure	19.6*	17.7**	12.1	10.1	0.19	0.79	-6.51	-1.32
	(10.3)	(8.23)	(21.9)	(19.2)	(6.67)	(6.22)	(12.1)	(8.35)
Business management and planning tools	23.0	19.8	15.9	13.6	11.8	12.8	11.0	7.54
	(16.0)	(12.3)	(11.6)	(13.0)	(12.8)	(12.6)	(14.2)	(12.8)
Cloud computing infrastructure	47.8***	45.7***	22.2**	25.2**	6.13*	4.92	-14.0***	-7.51
	(9.08)	(8.72)	(9.54)	(11.8)	(3.37)	(3.04)	(4.86)	(5.72)
Communication and collobaration tools	21.5**	21.0**	13.5*	11.1	0.79	2.23	-1.11	0.33
	(9.33)	(8.86)	(6.96)	(7.60)	(3.69)	(3.70)	(5.97)	(5.43)
Data analytics and visualization	19.9**	20.0**	-10.2	-11.4	-5.48	-4.88	0.014	1.97
	(9.37)	(8.11)	(24.1)	(25.7)	(4.80)	(4.54)	(5.81)	(5.48)
E–commerce and customer interaction	1.84	-0.24	2.92	-0.42	3.53	3.86	-5.18	-8.47
	(5.83)	(5.68)	(8.74)	(8.09)	(4.99)	(5.25)	(10.0)	(7.06)
Process automation	3.76	5.90	-26.3	-30.8*	-7.91*	-7.36	-4.84	-14.0
	(11.8)	(11.7)	(19.0)	(16.8)	(4.70)	(4.70)	(10.1)	(14.4)
Observations	2,214	2,214	2,213	2,213	2,213	2,213	2,145	2,145
R-squared	0.35	0.40	0.15	0.17	0.14	0.16	0.26	0.39
Mean of dependent variable	15.0	15.0	-6.1	-6.1	-3.0	-3.0	10.9	10.9
Covid controls		✓		✓		✓		✓

Notes: The table reports results from regressing changes in employment indicators 2019–2022 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 A8. Regressions are weighted using sampling weights. Robust standard errors in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

Table A8: Firm-level Covid exposure and investments in office & communication equipment

	Reason & timing			*Change in frontier technology share*				
			During,	2016–22				2022–27
	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 A9: Firm-level Covid exposure and investments in office & communication equipment (employment weights)

	Reason & timing			*Change in frontier technology share*				
			During,	2016–22				2022–27
	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 A10: Firm-level Covid exposure and investments in production equipment

	Reason & timing			*Change in frontier technology share*				
				2016–22				2022–27
	Due to	Pre	During, 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).[30]

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.[31] 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

[30]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/`.

[31]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

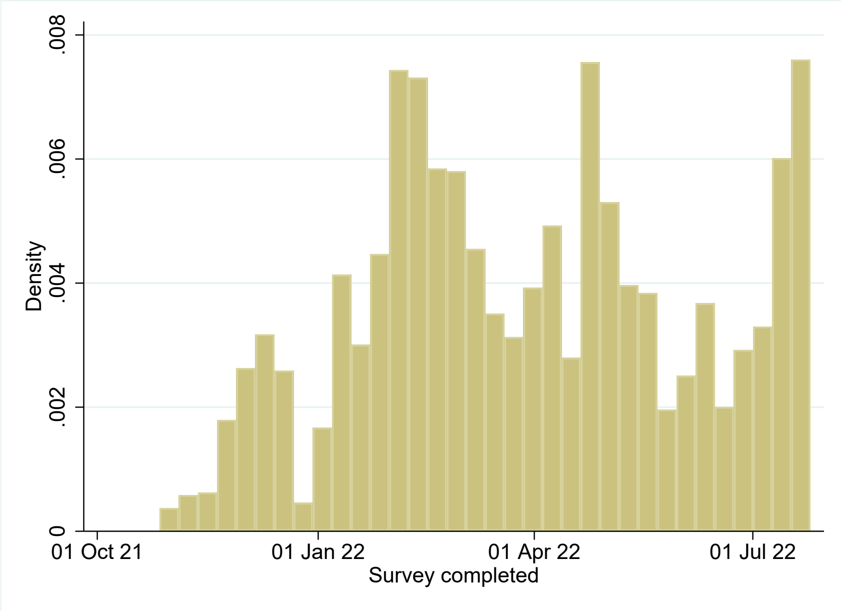
average, the interviews lasted 30 minutes and took place between October 2021 and July 2022. Figure B1 shows the distribution of interview dates.

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.[32] 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.[33] We use

[32]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).

[33]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



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 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).[34]

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.[35] 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.[36] 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 2022 (3,851,063 observations for 721,332 employees). 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[37], occupation and industry. We use this data to study employment changes at the firm level. For this, we calculate the overall employment for the years 2019–2022 as the total number of full-time equivalent working days of all employees within a firm and calendar year.[38]

[34]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).

[35]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.

[36]Alternatively, Hensvik et al. (2020) directly measure realized working from home rates by occupations and industries in the US.

[37]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).

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

In order to obtain firm characteristics that serve as controls in later analyses, we further use employment spells from social insurance records (IAB Beschäftigtenhistorik (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 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 A8 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 2016–2022 (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 A9). For production equipment, none of the variables appear to be predictive of technology adoption (Table A10).

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.

D 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 2016–2022. 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*:

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

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 (D.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.