CESifo WORKING PAPERS

11114
2024

May 2024

Local Labour Market Resilience: The Role of Digitalisation and Working from Home

Sarra Ben Yahmed, Francesco Berlingieri, Eduard Brüll

CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editor: Clemens Fuest
https://www.cesifo.org/en/wp
An electronic version of the paper may be downloaded
· from the SSRN website: www.SSRN.com
· from the RePEc website: www.RePEc.org
· from the CESifo website: https://www.cesifo.org/en/wp

CESifo *Working Paper No. 11114*

Local Labour Market Resilience: The Role of Digitalisation and Working from Home

Abstract

We show that digital capital and working from home were essential for the resilience of local labour markets in the context of the COVID-19 crisis in Germany. Employment responses differed widely across local labour markets, with differences in short-time work rates of up to 30 percentage points at the beginning of the pandemic. Using recent advancements in the difference-in-differences approach with a continuous treatment, we find that pre-crisis digital capital potential reduced short-time work rate by up to 3 percentage points. The effect was nonlinear, disproportionately disadvantaging regions at the lower end of the digital capital distribution for a longer period. One channel of impact is working from home, which was more often adopted in regions with higher digital capital. But digital capital smoothed the employment shock beyond the effect of remote work.

JEL-Codes: J210, O300, R120, R230.

Keywords: Covid-19, crisis, digitalisation, employment, information and communication technologies, local labour markets, resilience, short-time work, working from home.

Sarra Ben Yahmed
ZEW Mannheim / Germany
Sarra.BenYahmed@zew.de

Francesco Berlingieri
European Commission, JRC
Ispra / Italy
Francesco.Berlingieri1@ec.europa.eu

Eduard Brüll
ZEW Mannheim / Germany
Eduard.Bruell@zew.de

April, 2024
We would like to thank Melanie Arntz, Louis Knüpfling, Harald Fadinger, Jan Schymik, Rolf Sternberg, as well as seminar participants at ZEW and IAB for valuable feedback. This research was conducted as part of the DFG project ”Regional Economic Disparities in the Aftermath of the COVID-19 Outbreak: the role of Digitalisation and Working from home” (project number 458454974). We gratefully acknowledge the financial support from the German Science Foundation. Opinions expressed herein are those of the authors only and do not reflect the views of, or involve any responsibility for, the institutions to which they are affiliated. We are responsible for all remaining errors.

1 Introduction

Digitalisation has spurred productivity growth and transformed the nature of work over the past few decades.[1] It has also proven to be indispensable for socioeconomic resilience, providing crucial support for rapid recoveries in the wake of economic shocks for firms for firms (Comin et al., 2022; Bai et al., 2021; Doerr et al., 2021; Bertschek et al., 2019), individuals (e.g., Adams-Prassl et al., 2020; Chiou and Tucker, 2020) and regions (e.g., Alipour et al., 2021; Reveiu et al., 2023; Oikonomou et al., 2023). Indeed, digital capital is essential to firms' organisational flexibility, fast reaction to disruptions in supply chains and changes in demand, and workers' ability to work and interact remotely. Digital capital likely played a crucial role in managing the sudden and unprecedented labour market downturn during the COVID-19 pandemic, due to the sector shutdowns. In fact, about 30% of German firms reported that they invested (more) in digital technologies because of the pandemic (Bellmann et al., 2021). Working from home practices were widely adopted in the early phases of the pandemic (Barrero et al., 2021) and have been found to protect individuals against job loss (e.g., Adams-Prassl et al., 2020). However, digital capital endowments before the crisis have varied across regions and firms (Forman et al., 2012; Bellmann et al., 2021). This paper analyses to what extent digital capital shielded local labour markets from the pandemic crisis.

Local labour markets disparities in their response to the COVID-19 crisis were massive. In Germany, relatively few workers have lost their job at the onset of the pandemic, but many have been asked to reduce their working hours within short-time work (STW) schemes that have been extended in generosity and coverage (Adams-Prassl et al., 2020).[2] As a result, the share of employees in short-time work spiked to 18% in April 2020. However, the average increases in short-time work rates hid wide differences across local labour markets, ranging from 9 to almost 38 percentage points. The unemployment rate also increased but by much smaller magnitudes.

In this paper, we investigate how local employment responses in 2020 and 2021 in Germany have been affected by the pre-crisis local potential exposure to digital capital and working from home. More precisely, we study local labour markets' responses in both short-time work and unemployment rates over the course of more than a year using detailed administrative data at the county level. To the best of our knowledge, this paper is the first to analyse the medium-run consequences of local digital capital on local employment responses to the crisis. Given the existing spatial digital divide, it is crucial to understand how it affects regions' capacity to recover from a shock over time. There is evidence that previous recessions tended to exacerbate

[1] See Gal et al. (2019) and Munch et al. (2018) for recent reviews of the literature.

[2] In Germany, like in many other countries, employees in short-time work schemes are compensated by the government for the wage loss due to the decrease in working hours. During the pandemic, the maximum duration of this scheme was extended from 12 to 28 months.

regional disparities.[3] However, the effect of the COVID-19 crisis on regional disparities has not been yet studied, apart from a few papers using data from the very early phase of the pandemic. A peculiarity of the COVID-19 pandemic is the unique role that digital technologies have played.

To analyse the role of digitalisation on local employment, we employ the latest advances in difference-in-differences techniques to accommodate a continuous treatment. The intensity of the treatment depends on a region's pre-crisis exposure to digital capital and working from home. Local investments in digital capital and adoption of remote work are likely related to other local characteristics that also affect labour market resilience. To estimate the causal effects of digital capital and remote work on local employment responses to the crisis, we construct two exposure measures that do not depend on regions' adoption of digital technologies. To measure a region's exposure to digital capital, we use pre-crisis data on information and communications technologies (ICT) capital in German industries and weight it with the region's employment shares in these industries. we define this measure as the digital capital potential of a region. To measure a region's working from home potential, we follow the existing literature and weight pre-crisis working from home frequency for detailed occupations by the region's employment shares across these detailed occupations. Moreover, we control for systematic differences across regions using a propensity score weighting procedure. By doing so, we compare regions with similar 1-digit industry mix, GDP per capita, demographic characteristics, labour market characteristics and product market characteristics. In particular, we show that after the weighting procedure local labour markets are similar in terms of many aspects that influenced the impact of the COVID-19 crisis, such as the employment share of the hospitality sector, the number of tourist stays, participation in the global value chain, and the contact intensity of the workforce. In addition, we use instrumental variables to estimate with an alternative empirical approach the causal impact of digital capital potential on the local employment responses over time.

We first show that German local labour markets had vastly different employment responses to the COVID-19 crisis. The differences in short-time work rates were very large in the short run, and smaller differences persisted in the medium run. Unemployment differences were smaller but persistent. While the short-run employment responses to the COVID-19 pandemic and the regional differences were unprecedented, local labour markets in Germany have quickly converged to similar and lower short-time work rates and reached pre-crisis unemployment levels by summer 2021.

We find that local exposure to digital capital before the start of the pandemic reduced short-time work usage for more than a year. An increase in digital capital potential by one standard deviation (around €213 per worker) led to a reduction in short-time work by 1.5

[3] See for example Yagan (2019); Hershbein and Kahn (2018); Hershbein and Stuart (2023).

percentage points, or roughly 9%. However, this overall effect conceals significant regional disparities; specifically, regions within the lowest decile of digital capital potential faced short-time work rates almost 4 percentage points, or roughly 23%, above the overall regional average in Spring 2020. Additionally, a one standard deviation in the work from home potential led to a 1.5 percentage point (ca. 9%) decrease in short-time work rate at the onset of the first lockdown. This effect was mostly linear with similar magnitudes all along the bottom part of the WfH distribution. After the relaxation of the first lockdown restrictions (end of June 2020), a region's working from home potential had only minimal effects on its employment outcomes, even if remote work remained a common practice. The effect faded completely after eight months. Moreover, we find that digital capital was necessary for remote work to save jobs. First, local digital capital potential increased the adoption of remote work after the shock. Second, controlling for both digital capital and working from home potential in the same regression, we find that digital capital keeps on having a strong and persistent effect. However, the effect of working from home turns insignificant, suggesting that part of its effect is due to digital capital potential, supporting the complementary of digital capital and working from home.

This paper contributes to the literature that examines the impact of economic shocks across regional labour markets, specifically complementing early papers on the labour market impact of the COVID-19 pandemic that used individual surveys and/or focused on the short-run effects of the pandemic. In particular, the paper is closely related to work on the role of digital capital (Oikonomou et al., 2023) and working from home potential (Alipour et al., 2021) in the first two months of the pandemic. First, we extend the time horizon, as it is essential to know whether a spatial digital divide before a crisis leads to a widening of spatial inequalities in the medium-run, making digital capital essential to resilience, and policy intervention even more necessary during and after the crisis. Second, we explore to what extent digital capital was a pre-condition for working from home to help save jobs. Finally, we study the role of digital capital in Germany, thus complementing evidence for the US, a country, where the labour market institutions and social protection schemes are markedly different. In Germany, the spatial digital divide brought further employment inequalities with the pandemic. But the effect was concentrated on short-time work rates in the short to medium run. Low digital capital regions did not register higher unemployment rates. The higher use of short-time work in local labour markets with low digital capital, together with high job-to-job transitions out of badly hit sectors, has likely prevented longer-term increases in unemployment.

The rest of the paper is organised as follows: in section 2 we review the literature on past recessions or pandemics on local labour markets and existing findings on the COVID-19 pandemic, employment responses and inequality across regions. Section 3 describes the data and provides some facts and trends on short-time work and unemployment responses across local labour markets. We discuss the empirical strategy in section 4. The results are presented in section 5, followed by a discussion of the findings and avenues for future research in section 6. The last section concludes.

2 Literature review

2.1 Labour markets' responses to shocks

This paper contributes to the literature on local exposure to shocks and local labour markets. Past recessions, including the last major recession of 2007-2009, had long-lasting impacts on regional employment levels, causing long-term declines in employment in more-affected regions (Yagan, 2019; Hershbein and Stuart, 2023, for the U.S.). Moreover, there is evidence that shocks due to past pandemics increased inequality within countries, and that the effects on vulnerable workers vary across countries depending on their socio-economic conditions like the distribution of education and growth rates, but also the institutional setting and social policies in place (Furceri et al., 2022; Ma et al., 2020). By investigating medium-term employment effects of the COVID-19 crisis across German regions, we provide early evidence on the impact of this crisis on regional disparities.

The COVID-19 crisis has had a wide impact on the labour market. Several studies have analysed its effects on the employment of various population groups, revealing that less-educated workers and women have been the most affected (see, e.g., Adams-Prassl et al., 2020; Hershbein and Holzer, 2021; Lemieux et al., 2020). The COVID-19 pandemic has impacted different sectors and individuals compared to previous recessions, with the largest impact in high-contact service sectors such as restaurants, hospitality, and travel (Alon et al., 2022). Non-pharmaceutical interventions, such as restrictions for restaurants and bars and closures of non-essential businesses, have contributed to the increase in unemployment in many countries, especially in the first few months after the pandemic outbreak. While their contribution has been documented to be small in the US (Kong and Prinz, 2020), there is some indication that lockdown measures have been a major cause of the increase in unemployment in Germany (Bauer and Weber, 2020). However, this increase in unemployment has been relatively modest in Germany, while the crisis has instead led to a substantial rise in short-time work (Adams-Prassl et al., 2020). We show for the first time that both the short-time work and unemployment responses varied widely across local labour markets in Germany, with short-time work rates differences of up to 20 percentage points in spring 2020. The German labour market had shown similar responses in previous recessions, with widely used short-time work schemes and limited unemployment (Burda and Hunt, 2011), but the responses to the pandemic were magnitudes larger , as we document in Section 3. The short-time work rate spiked to 18% on average in April 2020. In more than a quarter of the German local labour markets, short-time work was used by more than 20% of individuals in employment before the pandemic.

Given the exogeneity of the shock to businesses and workers, short-time work may be a successful policy to safeguard employment in the current crisis, and an optimal one from a welfare point of view (Giupponi and Landais, 2022). Nevertheless, by reducing working hours and wages, it also comes at a cost for workers. Herzog-Stein et al. (2021) estimate that the average German short-time worker faced a total income loss of almost 20% in April 2020.

Our paper is mostly related to the limited number of papers who have looked at local labour markets or exploited regional differences in the early phases of the COVID-19 pandemic. Aum et al. (2021) find that an increase in infections led to a drop in local employment even in the absence of lockdown, such as in South Korea, but that the effect was higher in the US and the UK, countries where mandatory lockdowns were imposed. For Germany, Bauer and Weber (2020) show that regional variation in exposure to lockdowns and infection rates led to variation in unemployment rates in April 2020 while Hamann et al. (2023) find more adverse employment effects in large agglomerations compared to rural regions in 2021. Surprisingly, Forsythe et al. (2020) find that the reductions in job vacancies were uniform across the U.S., without notable differences between states with different timing in the spread of the pandemic or in the implementation of lockdown measures.

2.2 The role of digital technologies and remote work in recessions

Digital technologies have been shown to be an important factor for resilience to a crisis. Research on previous recessions has documented the fact that ICT-intensive firms were hit less hard by economic shocks and were also more successful in introducing process innovation during the crisis (Bertschek et al., 2019). Moreover, Pierri and Timmer (2022) show that ICT adoption in the financial sector has been important for resilience and credit provision during the global financial crisis. At the regional level, Reveiu et al. (2023) provide evidence that different measures of digital development proved to be important for labour market resilience during the Great Recession. Evidence on the short-run response of unemployment in the US shows that States where firms adopted more ICT even long before the crisis had lower unemployment rate in spring 2020 (Oikonomou et al., 2023).

Arguably, the role of digital capital has been even more important in the 2020 pandemic recession compared to previous crises due to the implementation of health and safety measures, such as lockdowns and self-isolation measures. Digital capital has helped companies to reorganise work arrangements and production processes more quickly and to increase online sales (Comin et al., 2022). Moreover, manufacturing firms that had automated processes before the crisis may face fewer safety issues due to less human contact and thus have fewer disruptions in production.

A further important reason why technology mattered during the pandemic recession is that it facilitated remote work. Due to non-pharmaceutical interventions and to prevent health risks, many workers started to work from home (WfH) shortly after the COVID-19 outbreak. According to survey data, the percentage of days worked from home increased from circa 5% in 2018 to more than 60% in April 2020 in the US (Barrero et al., 2021) while the share of employees working entirely from home reached 43% in Germany in May 2020 (Frodermann et al., 2021). Several papers have documented how workers in occupations that allow for remote work faced a lower likelihood of losing their job or being in short-time work schemes (Adams-Prassl et al., 2020; Béland et al., 2023). This reinforced existing inequalities, as WfH is less likely to be feasible for low-skill, low-wage occupations in both manufacturing and services (Adams-Prassl et al., 2022).

At the regional level, Crescenzi et al. (2022) show that in Italy, Northern regions had more employees working from home compared to Southern regions throughout 2020, which can be explained not only by differences in industry composition but also by differences in the adoption of digital technologies. Overall, the task-based measure of WfH potential largely overestimates actual WfH in regions with lower GDP and lower living standards. In fact, even before the COVID-19 crisis, workers were less likely to work from home in poorer regions, as shown in Irlacher and Koch (2021) for Germany. As a result, the pandemic crisis may have amplified regional disparities due to differences in WfH feasibility. It is thus essential to account for local specificities such as the digital divide when studying how WfH may help local resilience during a crisis. Alipour et al. (2021) present evidence that German districts with a higher share of teleworkable jobs experienced fewer short-time work registrations and fewer SARS-CoV-2 cases in April and May 2020. They do not investigate further which local characteristics may have shaped the adoption of WfH. In this paper, we complement and extend their findings by investigating how the role of other regional disparities, in particular local exposure to digital capital, has shaped the impact of WfH on employment. In addition, we study how the impact evolved over the year that followed the pandemic outbreak and analyse the heterogeneous responses along the regional distribution of the WfH potential.

Whether tasks can be productively and quickly carried out from home instead of from the workplace, does not only depend on the teleworkability of a job, but also on whether the required technology is available. For instance, remote work in many jobs requires a well/functioning Virtual Private Network (VPN) system and adequate ICT support. Investing in these technologies and processes may require time and previous knowledge as well as experience. In fact, there is evidence that firms invested extensively in digital technologies after the pandemic outbreak, but that larger and more innovative firms invested comparatively more (Arntz et al., 2023b; Bellmann et al., 2021; Gathmann et al., 2023; Valero et al., 2021). The rising need for digital technologies since the pandemic is evidenced by the increase in the share of digital jobs among new vacancies, as shown by Oikonomou et al. (2023) for the US.

The importance of technology during the crisis may also matter for regional disparities. It has been shown that the process of digitalisation is not spatially neutral, but affects regions within the same country to varying degrees. For instance, there is evidence from the US that the regional gains from first generation of ICT were concentrated in a few counties with high income and high skill levels, thus exacerbating wage inequality across regions (Forman et al., 2012). Thus, differences in the pre-crisis ICT endowments between richer and poorer regions could potentially lead to an increase in regional disparities in the aftermath of the COVID-19 pandemic recession.

3 Data and descriptive statistics

3.1 Employment data

We combine several sources of data from the Federal Employment Agency, which publishes monthly reports (*Arbeitsmarktreport*) with detailed information on county-specific labour markets (NUTS 3 level). These regional employment statistics are calculated directly from German social security records, which makes the results of our regional analyses easily comparable to microdata-based approaches. These are the first data sets available for detailed regional analyses and are well suited to investigate the impact of the recession on local labour markets in a timely manner.

Monthly reports on short-time work are available at the county and industry level. The industry classification is between 1 and 2 digits and, for confidentiality reasons, is rarely available at a more disaggregated level within counties . This data permits the disentangling of the role of a region's industry mix from its employment response within industries. Moreover, there are two different types of short-time work in Germany: seasonal short-time work (used mostly by specific industries in the winter) and business-cycle-related short-time work, which is more relevant for the COVID-19 crisis. Therefore, in this paper we concentrate exclusively on business-cycle-related short-time work.

The employment measures are based on different geographic concepts. The unemployment and employment data rely on a residence concept. However, the data on realised short-time work are based on a place-of-work concept, as the Federal Employment Agency uses reports by employers to aggregate statistics at the county level from the job location (i.e. the address of an employer that requests short-time work for her/his employees).

To avoid potential problems arising from combining residence- and job-based measures, we aggregate county-level data into 257 labour market regions, which were delineated by Kropp and Schwengler (2016) based on commuting patterns. Moreover, by using labour market regions as the geographic level of analysis, we group together counties that have strong economic links, and similar industry structures, and should therefore respond similarly to the shock of COVID-19.

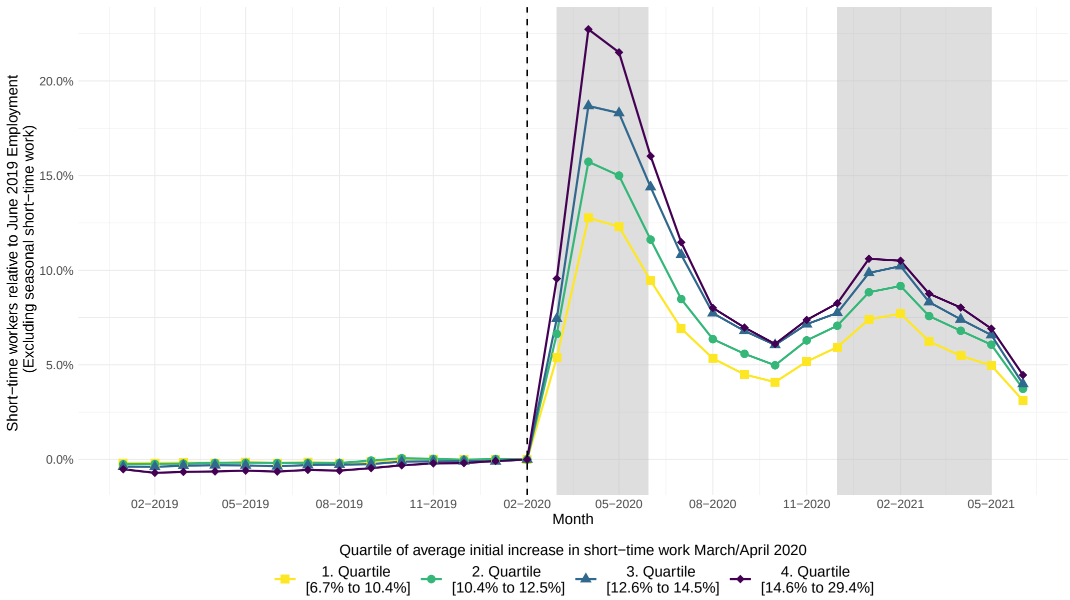
3.2 Employment responses across local labour markets

Local labour markets had different employment responses, especially at the onset of the pandemic. Figure 1 shows the evolution of short-time work usage over time for four groups of labour market regions ranked by their initial increase in short-time work rate. Short-time work rates saw sharp increases in March and April 2020, with strong regional discrepancies. In April 2020, differences in short-time work rates across local labour markets were as high as 25 percentage points. Regions within in the first quartile of the initial short-time work increase had short-time work rates below 10.4 %, while 14.5% to 29.4% of workers were in short-time work in the most affected regions. After this initial increase, short-time work rates declined until October 2020 when the regional differences had reduced to about 3 percentage points. Short-time work rates increased again during the second lockdown, but regional differences remained stable. After the winter, short-time work rates and their regional differences declined even further.

In Germany, short-time work has been the margin of adjustment of labour markets during the COVID-19 crisis. Contrary to short-time work, unemployment increased only by small magnitudes. The highest regional increases ranged from 0.2 to 2.7 percentage points in August 2020 relative to August 2019 (Figure 1 in the appendix). Moreover, it was back to pre-crisis levels in all regions by summer 2021. Given the small response of unemployment, we focus on local short-time work variation in the rest of the paper.

The effect of the crisis on employment varied greatly across sectors of the economy. The hospitality industry was affected the most. In section B of the appendix, we compute a decomposition and show that regional differences in STW are mostly driven by differences in STW rates within 5 broad industries (construction, manufacturing, retail, hospitality, and other services). Regional differences in STW are not driven by regional differences in broad industry mix. In the rest of the paper, we study how the exposure to digital capital influenced regional differences in short-time work *within* these broad industries. As explained in section 4, we do so by i) using information on local employment and digital capital for more detailed industry

Figure 1: Changes in short-time work across local labour markets



NOTE.- The figure depicts the short-time work rates of regions relative to February 2020 grouped by quartiles of the average increase of short-time work in March/April relative to the previous year. The periods of the two lockdowns in Germany in spring 2020 and the winter from 2020 to 2021 are marked in grey. Short-time work rates are calculated as the number of workers using short-time work in business-cycle-related short-time work in a given month over the employment level in June 2019.

groups (40 industries, including 13 manufacturing industries) and ii) controlling for the local employment shares in the 1-digit manufacturing, construction, retail and hospitality industries.

3.3 Data on digital capital and working from home

To compute the local exposure to digital capital, we use industry-level data of capital stock in information and communication technologies (ICT) equipment for 2019 from the EUKLEMS database.[4] Our measure of ICT capital combines computing equipment capital and communications equipment capital. Therefore, it includes therefore computer hardware, such as computers and storage devices, as well as telecommunications equipment, such as mobile devices and routers. Moreover, as a separate measure, we also use other machinery and equipment, which includes different types of non-ICT and non-transport machinery and equipment, such as machinery used in manufacturing, non-ICT office equipment, etc. EUKLEMS capital data is available for 40 2-digit industries for Germany. While the main sources of the data are Eurostat or the German Federal Statistical Office, the breakdown by industry is not available for all years and asset types. The main advantage of the dataset is that missing data is imputed consistently through an iterative bi-proportional fitting procedure using totals by industry and totals by

[4] We use the 2021 release of the data that can be downloaded from the EUKLEMS & INTANProd website: https://euklems-intanprod-llee.luiss.it/

asset from official sources (Bontadini et al., 2023).

To compute the local exposure to WfH, we use occupational-level data on working from home frequency in 2018 from the last wave of the BIBB/BAuA Employment Survey. The survey is described in Rohrbach-Schmidt and Hall (2020). It asks workers whether they had been working from home regularly. We also know the occupation of a worker at the detailed 3-digit level. Similarly to Alipour et al. (2021), we compute the 2018 average frequency of WfH for each 3-digit occupation to identify jobs for which remote work had been used just before the crisis. Alipour et al. (2023) compare the WfH potential constructed using information from the BIBB/BAuA Employment Survey to actual implementation of WfH in 2020 and find that the measure is a good predictor of actual WfH use.

3.4 Other regional-level data

Apart from data on employment, digital capital and working from home, we use data at the regional level from different sources. First, county level data on population, population density, GDP per capita for 2019 are taken from the German Covid-19 data platform (i.e. *Corona-Datenplattform*) which combines data at the county level from several official sources. Second, data on employment by education, firm size, (1-digit) industry and county for 2019 come from the Federal Employment Agency. Third, we use survey data on ICT skills from the Programme for the International Assessment of Adult Competences (PIAAC) to compute a regional-level index of ICT-skills.[5] We do this by computing industry-level averages and weighting these by the industry local employment share, in a similar manner as for the treatment variables.

4 Empirical strategy

4.1 Local exposure to digitalisation

We construct two measures of local exposure to digitalisation: the exposure to digital capital and the exposure to remote work.

Digital capital potential: The measure of local labour market exposure to digital capital uses pre-crisis (2019) data on employment at the county and industry level and data on ICT capital at the national and industry level.[6] We construct a measure of regional potential for digital capital per worker just before the pandemic. To do so, we first compute the industry-specific digital capital per worker in Germany for each industry i, $K_{ICT,i}$, and we multiply it by

[5] The PIAAC survey was conducted in 2011 and 2012 in Germany and provides a measure of cognitive skills in the ICT domain (called "problem solving in technology-rich environments" in the survey) for circa 3400 employed individuals.

[6] The list of 40 industries is given in Table B.1 in the appendix.

the share of industry i employment in region r. We then compute the sum of this region-industry specific digital capital over all industries present in region r:

$$K_{ICT,r} = \sum_{i=1}^{I} \frac{E_{i,r}}{E_{\text{total},r}} \times \frac{K_{ICT,i}}{E_{i,\text{national}}} \tag{1}$$

Equation (1) makes clear that the difference in $K_{ICT,r}$ across local labour markets stems entirely from variation in local industry employment structure just before the pandemic. This variation arises from specialisation in ICT-intensive industries at the regional level. The measure does not capture variation in digital capital within detailed industry across local labour markets. These variations would likely be endogenous to other regional characteristics, including characteristics that are difficult to control for, such as average manager quality. Our measure approximates the average potential for digital capital of a region given its industry structure and the national average digital capital of these industries. In other words, if an industry has a high level of digital capital at the national level, the local level of digital capital per worker within this industry could feasibly reach a similar amount in any region. The measure abstracts from the fact that some regions were lagging behind while others were forerunners in digital adoption.

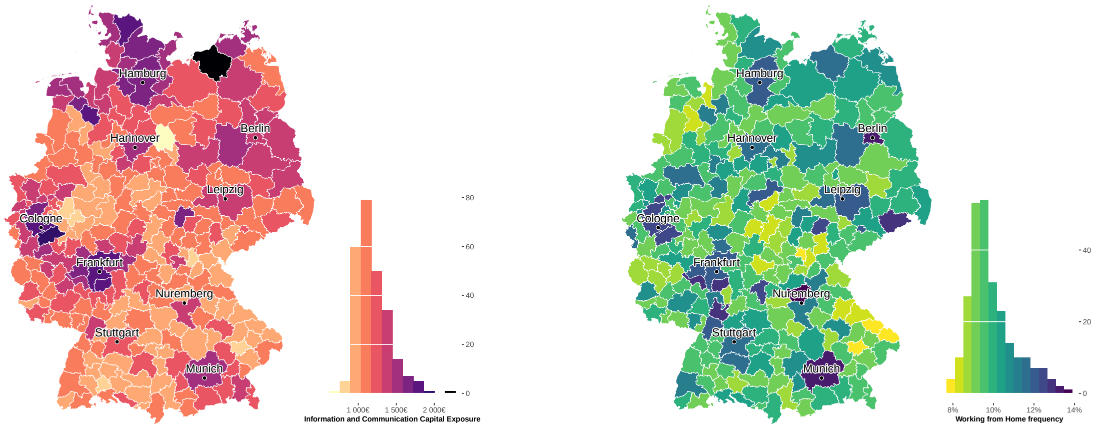
Using this exposure measure, we can exploit a wide variation in digital capital across German labour market. Figure 2a presents a map of the exposure to digital capital per worker. The average digital capital per worker across German regions is 1184 €. The large urban centres are at the top of the distribution, where the digital capital value is higher than 1500 € per worker. Smaller and more rural regions are typically at the lower end of the distribution with a digital capital below 1000€ per worker.

Working from home potential: The local WfH potential is based on data on actual working from home practices at the detailed occupation level in Germany before the pandemic. Similar to Alipour et al. (2023), we use data from the 2018 BIBB/BAuA Employment Survey and compute the average frequency of pre-crisis WfH for each 3-digit occupation. To compute the local WfH potential, we weight the occupation-specific WfH frequency with the local employment share of each occupation:

$$WfH_r = \sum_{o=1}^{O} \frac{E_{o,r}}{E_{\text{total},r}} \times \frac{WfH_o}{E_{o,\text{national}}} \tag{2}$$

Figure 2b shows that local labour markets vary in their working from home potential. The exposure to WfH is highest in large urban regions, which include the largest cities in Germany. The regions with the highest exposure to WfH are Berlin, Munich and Erlangen, with jobs in

Figure 2: Maps of digital capital and working from home potential across local labour markets



(a) Digital capital potential

(b) Working from home potential

NOTE.- Map (a) shows the average pre-crisis local digital capital potential per capita as constructed as in equation (1). Map (b) shows the average pre-crisis local working from home potential as constructed as in equation (2) for all 257 labour market regions.

which roughly 13.5% of workers reported to have regularly worked from home in 2018. Conversely, rural regions in the north and centre east have a smaller WfH potential with jobs for which less than 9% of workers reported to have regularly worked remotely before the pandemic.

4.2 Difference-in-differences with a continuous treatment and inverse probability weighting

Our empirical strategy combines a difference-in-differences strategy with a continuous exposure and inverse probability weighting. As the COVID-19 crisis affected all regions simultaneously and all regions already had some digital capital and teleworkable jobs, we do not observe an untreated group of regions. In other words, the treatment is not binary but continuous. Therefore, we compare how outcomes have evolved over time for regions with different intensities of digitalisation and working from home potential.[7] The strategy then allows to identify the effects of local exposure to digitalisation and to working from home on short-time work and unemployment rates by making local labour markets comparable through the weighting approach.[8]

Main assumptions: In total, our empirical strategy relies on the following three main assumptions.

[7]Similar approaches with a continuous treatment that exploits geographic variation are widely used, see for example Card (1992); Mian and Sufi (2012); Berger et al. (2020).

[8]Combining a differences-in-differences approach with inverse probability weighting was first proposed by Abadie (2005).

i. Strong parallel trends: Since we do not observe any untreated region that we could use as a comparison group to identify exposure-level-specific treatment effects, we rely on the strong parallel trends assumption proposed by Callaway et al. (2021). In particular, we assume that regions at all exposure levels would have experienced the same trends in potential outcomes if they had been assigned to the same exposure level and the COVID-19 crisis had not occurred. As a first validation exercise, we estimate several event study specifications and check whether there are different pre-trends at different points of the exposure distribution. We do not find significant differential differences in short-time work for regions with different intensities of digital capital or working from home potential before the COVID-19 outbreak (see the first row of Table 1 and Table 3).

ii. Conditional independence assumption: Conditionally on the covariates, there should be no unobserved selection into specific levels of digital capital or WfH potential. This assumption is needed in order to attribute the observed estimated effects to digital capital or WfH and not to other characteristics associated with them, such as the employment and education structure. As described in the next section, we use a weighting approach and estimate event study specifications for a pseudo-population of regions whose characteristics do not correlate with their exposure to digitalisation. After weighting, the correlation between the two explanatory variables and other key characteristics becomes small, supporting the validity of the conditional independence assumption (see the discussion of Figure 3 below).

iii. Stable unit treatment value assumption: Finally, the last main assumption implies that the level of digitalisation and WfH potential in one region should not have had employment effects in other regions during the crisis. This assumption should be innocuous for short to mid-term analyses of employment responses in our setting. First, local labour markets as defined here are constructed to minimise commuting across local labour markets. Second, large migration or capital transfers between local labour markets would only happen over a longer time horizon in Germany. Stawarz et al. (2022) even document a drop in inter-county migration in 2020 compared to 2019.

Inverse probability weighting: We use an inverse probability weighting strategy methodology for continuous treatments: the non-parametric covariate balancing generalised propensity score (npCBGPS) by Fong et al. (2018). Details about the method can be found in Appendix C.

We apply separate weighting procedures for each treatment intensity (ICT capital and WfH potential) but include the same covariates in both. As control variables, we use information on the employment share of 1-digit industries (manufacturing, construction, retail, hospitality) and the share of jobs in essential industries during the pandemic to better account for industry-structure differences that might be particularly relevant during the COVID-19 crisis. We also control for industry characteristics weighted by the industry local employment share, using the same weighting approach as the one used to construct the treatment. These characteristics include machinery and equipment capital and the share workers with high and medium levels of education. To account for the higher adaptability of high-skilled jobs we also include the share of college-educated workers in a region. To disentangle the effects of digital capital from trade disruptions that might have affected similar regions, we include the global value chain integration of regions as defined by Wang et al. (2022) into our weighting specification.[9] Since firms and industries in some regions might be more used to the procedures related to short-time work, we include the peak in short-time work rate during the Great Recession in 2009 to address this issue. Moreover, since large firms are more likely to adopt WfH, to invest in ICT but also to use short-time work, we also include the share of firms with more than 250 employees. Lastly, in order to avoid comparisons across more and less agglomerated regions, we include population density, total population and the regional GDP per capita. The precise list of targeted covariates can be seen in Figure 3.

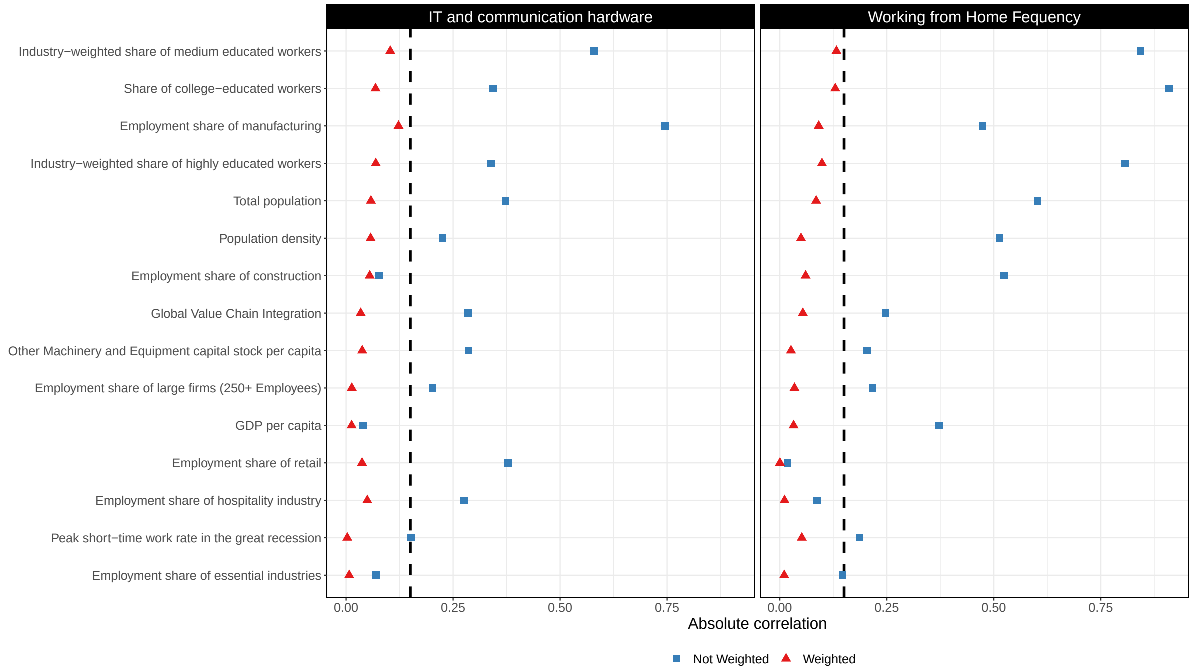
Figure 3 shows that the weighting method helps to achieve a very good balance of all targeted characteristics both along the digital capital and working from home potential distribution. In the left panel of the figure the blue squares show that digital capital potential is highly correlated with the employment share in manufacturing and the industry-weighted share of medium educated workers in the unweighted sample. Similarly, the left panel shows that the working from home potential has very high correlation (above 0.9) with the share of college educated workers. However, after weighting, the balance along key covariates is extremely good for both variables of interest. The red triangles report that the correlations in the generated pseudo-samples are always below 0.15 for all variables included in the weighting approach. Besides a strong improvement in the balance of the targeted characteristics, the weighting procedure also substantially increases balance in several relevant non-targeted dimensions, as shown in Figure C.1 in the appendix. After weighting, the correlations with both digital capital and working from home potential are always below 0.15 for all key variables reported in the figure. In particular, knowing that the pandemic led to a ”she-cession” in many countries, we show that after re-weighting regions have similar female employment and part-time employment shares.[10] Weighting also helps to achieve balance in other important characteristics such as the age structure of employment, registered internet domains and an industry-weighted index of ICT skills.

To ensure common support, we first trim the 5% of regions with the highest and lowest

[9]We thank Moritz Meister and Annekatrin Niebuhr for sharing the data with us.

[10]In Germany, as in a few other countries, women were just as affected by employment losses as men, but reduced working hours more (Alon et al., 2022; Bluedorn et al., 2023).

Figure 3: Balance plots for targeted covariates



NOTE.- The left panel shows the absolute correlations between covariates included in the inverse probability weighting approach and regional digital capital potential both in the unweighted (red triangles) and the weighted sample (blue squares). The right panel shows the absolute correlations between the same covariates and regional working from home potential.

weights. Second, we show that there are many regions at different values of the treatment in the adjusted sample (see Figure C.2 for digital capital and Figure C.3 for WfH potential in the appendix).

Event-study specification: We then estimate a standard event-study specification on the weighted sample. The regression includes region- and time- fixed effects, as well as treatment-time interactions:

$$\mathrm{Y}_{rt} = \sum_{t=-12, t\neq 0}^{T} \beta_t \textsc{Digitalisation}_r \times \textsc{Time}_t + \sum_{t=-12, t\neq 0}^{T} \gamma_t \textsc{Time}_t + \alpha_r + \varepsilon_{rt}. \tag{3}$$

where Y_{rt} is either the short-time work rate (i.e. the number of workers using short-time work in a given month divided by the employment level in June 2019) or the unemployment rate (i.e. the number of unemployed individuals in a given month over the employment level in June 2019) of region r in month t. $\textsc{Digitalisation}_r$ is the standardized value (z-score) of i) the local digital capital potential $K_{ICT,r}$ or ii) the local WfH potential WfH_r. We use February 2020 as the reference period because this coincides with the start of the spread of the coronavirus, while the first lockdown took effect by mid-March 2020 in Germany. We estimate the effect of the treatment over 16 months after the start of the pandemic and for the preceding 12 months to test for pre-trends. We estimate this event-study specification using npCBPS weights. In a second step we also estimate equation 3 where $\textsc{Digitalisation}_r$ is a binary variable equal to one for regions at the top of the local digital capital distribution or the local WfH potential distribution (i.e. top nine, eight, six or five deciles). Section 5 provides the results.

4.3 Instrumental variable approach

Our measure of the local digital capital potential depends on a region's industry mix and the industries' endowment in digital capital just before the shock. The approach we have described above to identify the causal effect of digital capital on employment hinges on the assumption that, conditional on the set of covariates, the local digital capital potential in 2019 does not correlate with other local characteristics that influence the employment responses to the shock. While we show that regions are similar in many dimensions after the weighting procedure, we cannot rule out that some unobservable characteristics are correlated with the digital capital measure. To address the risk of endogeneity bias, we provide evidence based on an instrumental variable approach.

We use two variables to instrument local digital capital potential in 2019. The first variable is the proportion of employees who frequently used computers back in 1979. Regions with a high percentage of workers in computer-intensive jobs during that time period were more likely to further invest in digital technologies. In the late 70s, computers were not yet widely adopted. We therefore argue that local computer use at this time reflects the technology advancement of the local industry structure and is unlikely related to today's labour market other than through the technology channel. The second instrument we use is the local routine employment share in 1979. It is based on Autor et al. (2003) who show that the computer technology substitutes for workers in performing routine tasks that can be readily described with programmed rules. As a result, regions with higher routine employment shares invested more in computers. Autor and Dorn (2013) argue that historical routine employment shares represents the long-run, quasi-fixed component of industrial structure. As such, they are an exogenous shifter of computer adoption, that is to say they are unlikely to affect employment outcomes today through other channels than technology. Oikonomou et al. (2023) make the same argument and use this variable to instrument for local IT capital when looking at employment during the pandemic in the US. In Germany, we find that the share of employees for whom calculation was a important tasks predicts subsequent computerisation very well. Using these two variables, we account for two dimensions of digital technologies: 1) those that were already complementing workers in certain jobs (IT-intensive jobs) three decades ago, and 2) those that have replaced workers who performed routine and easily codifiable tasks.

Historical data on workers' tasks and computer use come from the 1979 BIBB/BAuA Employment Survey, a representative survey on qualification, working conditions and detailed job characteristics of the German labour force.

We run separate regressions for each sub-period t on the unweighted sample of regions r:

$$\text{STW}_{rt} = \beta_t \text{DIGITALISATION}_r + \alpha_r + \varepsilon_{rt}. \tag{4}$$

where STW_{rt} is the short-time work rate in region r in period t and the endogenous variables DIGITALISATION_r is instrumented with one or both of the excluded instruments. We estimate the equation by two-stage least squares.

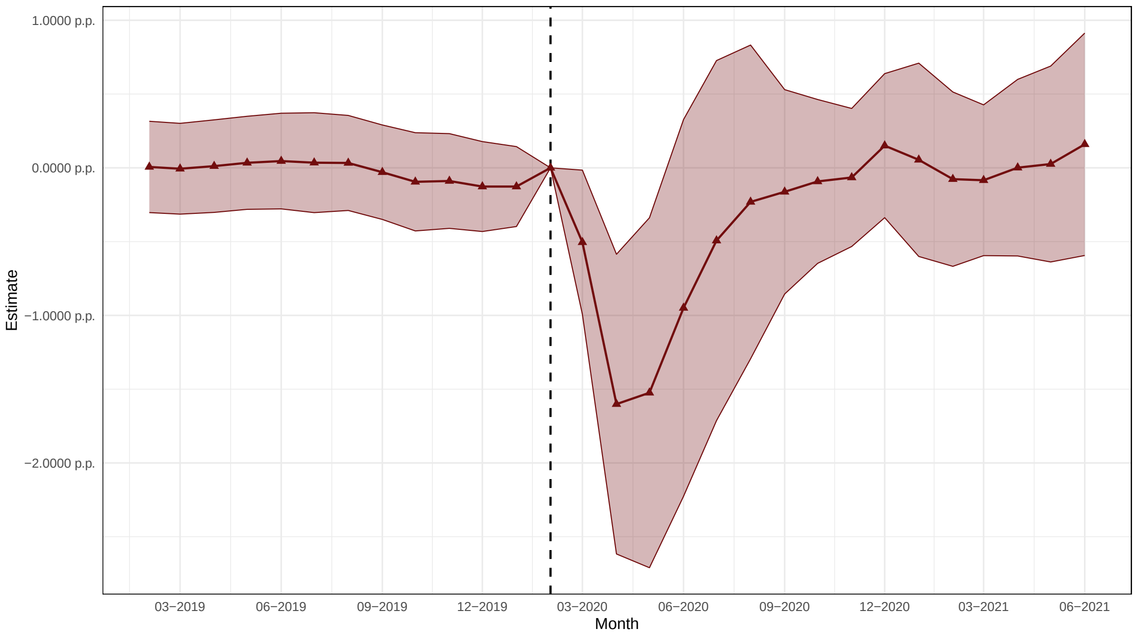
5 Results

5.1 Digital capital

We start by analysing how regions' pre-crisis exposure to digital capital impacted their labour market performance during the COVID-19 crisis. We first look at the short-time work response, which was the main margin of adjustment to the COVID-19-shock in the German labour market. We then look at the effect of digital capital on unemployment.

Short-time work rate: While our empirical strategy allows to estimate treatment effects over the whole distribution of digital capital, for simplicity, we first show the average impact of digital capital potential on the short-time work rate. In particular, we estimate equation (3) where DIGITALISATION_r is the standardized value (z-score) of the local digital capital potential. The estimates refer to the effect of a one-standard deviation increase in digital capital, that is 213€ per worker, on short-time work, in each month relative to February 2020. Figure 4 shows that the estimated coefficients are very close to zero for the months before February 2020, indicating that regions with low and high digital capital experienced parallel trends in short-time work rates prior to the COVID-19 pandemic. Right after the start of the pandemic, in spring 2020, regions with higher digital capital potential experienced a significantly lower incidence of short-time work. In April and May 2020, one-standard-deviation increase in digital capital corresponded to a 1.5 percentage point reduction in the short-time work rate. Given that the short-time work rate rose by 20 percentage points on average during these months, this corresponds to a reduction of approximately 8%. The average linear effect of digital capital potential gradually diminished in the summer of 2020, becoming small and insignificant after July 2020. Thus, local labour markets more exposed to digital capital were more able to adapt to the crisis and needed short-time work schemes to a lower extent.

Figure 4: Event-study estimates of digital capital on short-time work rates



NOTE.- The estimates measure the change in short-time work rates relative to February 2020 for a standard deviation increase in ICT capital. Short-time work rates are calculated as the number of workers using short-time work in a given month divided by the employment level in June 2019. The figure displays the 95% confidence intervals with the main estimate.

How does the impact of digital capital exposure change along the distribution? Table 1 shows that the results are strongest for the bottom of the digital capital distribution. Column 1 reports similar results to those of Figure 4 whereby the time periods are aggregated into one pre-event period and three post-event periods. Columns 2 to 5 report the results of estimating an event-study regression as in equation (3), where the event-study estimates now refer to an indicator variable of high local digital capital defined using various cut-offs points. The coefficients are largest for the difference between the bottom decile of digital capital potential and the other deciles (column 2). In the period from March to June 2020, short-time work rates are almost 4 percentage point lower in regions in the top nine deciles compared to those in the bottom decile, while they are 2.5 percentage point lower in the period between July and October 2020. When the median cut-off is used, the point estimate for spring 2020 is still significant but much smaller in size (see column 5). However, the impact appears to be longer lasting using this cutoff with a small impact of 0.7 percentage points for the period between November 2020 and June 2021. This provides some indication that digital capital did not matter only during the first lockdown but had a longer impact lasting until 2021. When using cut-offs above the median, the impact of digital capital becomes small and barely significant for any time period considered (see columns 7 and 8). Importantly, the coefficients for the period before February 2020 are small and insignificant in all specifications, confirming the validity of the strong parallel trends assumption. All in all, the results of Table 1 suggest that a relatively low level of regional digital capital potential was sufficient to protect many workers from entering short-time work schemes especially during 2020.

Table 1: Short-time work responses along the digital capital potential distribution

	(1) **z-score**	(2) **Over 10th pct.**	(3) **Over 20th pct.**	(4) **Over 30th pct.**	(5) **Over 40th pct.**	(6) **Over Median**	(7) **Over 60th pct.**	(8) **Over 80th pct.**
Before February 2020	−0.094	0.133	−0.008	−0.066	0.029	−0.060	−0.044	−0.640
	(0.156)	(0.204)	(0.098)	(0.092)	(0.094)	(0.106)	(0.145)	(0.564)
March to June 2020	−1.147**	−3.924***	−1.901***	−2.185***	−1.753***	−1.267**	−1.136*	−0.352
	(0.469)	(0.773)	(0.661)	(0.540)	(0.543)	(0.623)	(0.581)	(0.876)
July to October 2020	−0.245	−2.507***	−1.484**	−1.548***	−0.707*	−0.334	0.115	0.070
	(0.429)	(0.609)	(0.581)	(0.416)	(0.409)	(0.400)	(0.408)	(1.087)
Nov 2020 to Feb 2021	0.016	−0.629	−0.659**	−0.480*	−0.481	−0.752**	0.206	0.871*
	(0.265)	(0.527)	(0.330)	(0.288)	(0.322)	(0.366)	(0.333)	(0.471)
March to June 2021	0.026	−0.311	−0.587*	−0.264	−0.354	−0.733**	0.058	0.463
	(0.303)	(0.415)	(0.346)	(0.291)	(0.275)	(0.333)	(0.324)	(0.864)
Month fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Region fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
N	5654	5654	5654	5654	5654	5654	5654	5654
Adjusted R^2	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75

NOTE.- This table presents estimates of the difference-in-differences specification 3 with alternative definition for DIGITALISATION$_r$. In column (1), we use the continuous measure to estimate linear effects. To estimate the effect of digital capital along its distribution, we compute dichotomous variables equal to 1 if the local digital capital is greater than the pth percentile in columns (2) to (8).
$***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$

Short-time work rate results using instrumental variables: Table 2 provides instrumental variable (IV) estimates of the effect of digital capital on short-time work. Column (1) shows the results when using the historical share of computer use as instrument. The first-stage result reveals that the greater the computer use in 1979, the higher the digital capital potential today. More precisely, one standard deviation in local computer use in 1979 corresponds to half of a standard deviation in local digital capital potential in 2019. We report the robust (Kleibergen-Paap) F-statistics, which is just at the rule-of-thumb threshold of 10, supporting the strength of the IV. Looking at the second stage, we see that the average linear effect of digital capital is significant, with a one-standard-deviation increase in digital capital reducing the short-time work rate by 1.2 percentage points from March to June 2020. This estimate is very close to the previous estimate in column (1) of Table 1. Moreover, the IV results indicate that the linear effect of digital capital persists until October 2020, albeit with slightly smaller magnitudes.

Column (2) exhibits very similar results when using the historical share of routine employment as IV. The first stage result shows that a higher share of routine jobs in the past led to higher digital capital today, which is consistent with Autor et al. (2003) and Autor and Dorn (2013) for the US. The F-statistics is at 12, indicating that the IV is strong. Column (3) displays the results with both instruments. This specification gives similar and significant results for the effect of digital capital on short-time work rates, however the F-statistics indicates that the

Table 2: Short-time work responses to digital capital potential instrumented with historical determinants of digitalisation

	(1)	(2)	(3)
Before March 2020	-0.057^{***}	-0.064^{***}	-0.068^{***}
	(0.013)	(0.012)	(0.012)
March to June 2020	-1.263^{***}	-1.538^{***}	-1.663^{***}
	(0.392)	(0.363)	(0.36)
July to October 2020	-0.584^{***}	-0.823^{***}	-0.932^{***}
	(0.212)	(0.195)	(0.193)
Nov 2020 to Feb 2021	-0.235	-0.184	-0.16
	(0.182)	(0.168)	(0.167)
March to June 2021	0.051	0.078	0.09
	(0.169)	(0.157)	(0.156)
FIRST STAGE			
Constant	2.873^{***}	1.464^{**}	0.944
	(0.339)	(0.459)	(0.628)
Computer use in 1979	0.526^{***}		-0.283
	(0.065)		(0.233)
Share of routine employment in 1979		0.567^{***}	0.839^{***}
		(0.063)	(0.233)
First stage N	184	184	184
First stage R^2	0.27	0.31	0.32
F-statistics	9.88	12.22	6.27

NOTE.- This table presents estimates of equation 4. The continuous measure of local digital capital is instrumented by the local share of employees who often use a computer in column (1), by the local share of routine employment in 1979-measured with the prevalence of calculating tasks- in 1979 in column (2), and by both instruments in column (3). Note that each row in the upper part of the table presents estimates for a separate second stage estimation, while the second half of the table presents the common first stage used for all rows. The table reports the Kleibergen-Paap F-statistics.
$***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$

IVs are jointly weak. The IV results confirm our previous results that digital capital potential reduces short-time work rates.

Unemployment rate: One question that arises from these first two results is whether regions with low digital capital endowments also experienced higher unemployment increases or whether short-time work schemes and job mobility prevented unemployment increases in low digital regions. Figure A1 in the appendix shows that unemployment rates evolved in a similar way in regions with a low and high digital capital exposure. Regions with low digital capital endowments did not experience stronger increases in unemployment than other regions. Thus, the higher but temporary short-time work registrations in low-digital capital regions likely prevented a sharper rise in unemployment due to a temporary decline in employment demand during the first year of

Table 3: Short-time work responses along the working from home potential distribution

	(1) z-score	(2) Over 10th pct.	(3) Over 20th pct.	(4) Over 30th pct.	(5) Over 40th pct.	(6) Over Median	(7) Over 60th pct.	(8) Over 80th pct.
Before February 2020	−0.018	−0.056	0.052	−0.036	−0.011	−0.058	−0.074	−0.066
	(0.052)	(0.131)	(0.092)	(0.081)	(0.069)	(0.083)	(0.087)	(0.073)
March to June 2020	−1.189***	−1.261*	−1.151**	−1.337**	−0.998	−0.484	−0.787	−0.968
	(0.442)	(0.762)	(0.564)	(0.623)	(0.694)	(0.635)	(0.651)	(0.593)
July to October 2020	−0.740**	−0.719	−0.366	−0.478	−0.462	−0.326	−0.604	−0.696
	(0.348)	(0.589)	(0.428)	(0.591)	(0.489)	(0.504)	(0.515)	(0.471)
Nov 2020 to Feb 2021	−0.327	0.336	−0.319	−0.146	0.002	0.197	−0.122	−0.036
	(0.298)	(0.594)	(0.679)	(0.467)	(0.435)	(0.400)	(0.460)	(0.498)
March to June 2021	−0.092	0.246	−0.235	0.087	0.002	0.389	0.151	0.030
	(0.249)	(0.521)	(0.576)	(0.379)	(0.431)	(0.354)	(0.374)	(0.330)
Time-fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Region-fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
N	5654	5654	5654	5654	5654	5654	5654	5654
Adjusted R^2	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75

* p < 0.1, ** p < 0.05, *** p < 0.01

the pandemic. Moreover, job mobility increased significantly in 2020 among workers originally working in jobs that were hardly affected by the pandemic, in particular in the hospitality sector, as documented in Arntz et al. (2023a).

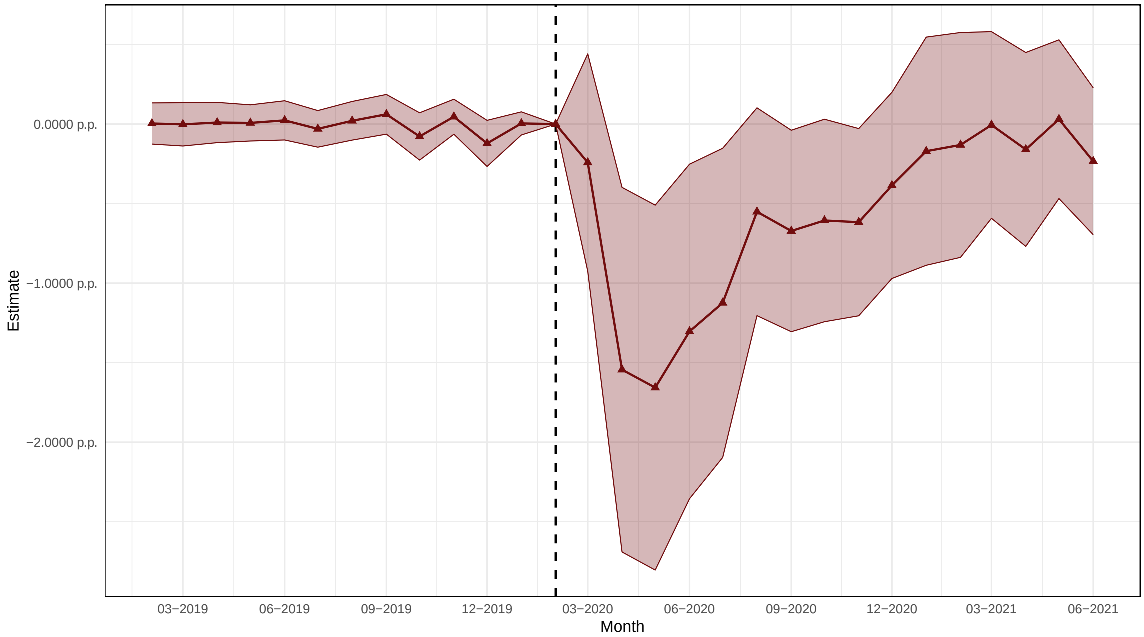
5.2 Working from home potential

One channel through which digitalization influenced labour markets during the pandemic was the ability to work remotely. The speed at which firms and their employees were able to efficiently implement remote work not only depended on the nature of tasks performed on the job but also on their pre-crisis experience in using such remote work arrangements. We thus investigate whether regions with a higher pre-crisis exposure to working from home benefitted in terms of lower short-time work and unemployment rates after the Covid-19 outbreak.

Short-time work rate: As for digital capital, we start by presenting the average results on short-time work rates for the event-study regression described in equation (3). Figure 5 shows that WfH had no impact on short-time work before the pandemic, confirming the parallel trends assumption. The impact of WfH potential on short-time work appears to be very similar of that of digital capital in spring 2020. A standard deviation higher WfH potential was associated with 1.5 p.p. lower short-time rates in May and June 2020. This confirms the results of Alipour et al. (2021). Moreover, the estimates decreased afterwards but were still significant until the end of 2020.

When looking at the results over the whole distribution of WfH potential in Table 3, we observe that the results are largest for regions at the bottom of the distribution, similarly to the results for digital capital. Columns 2 to 4 show that there are significant differences in March-June 2020 between regions up until the 30th percentile of WfH potential and other regions. However, we do not find any significant effect when comparing regions at other points in the distribution and the effect vanishes after the first lockdown.

Figure 5: Event-study estimates for working from home potential on short-time work rates



NOTE.- The estimates measure the change in short-time work rates relative to February 2020 for a standard deviation increase in working from home potential. Short-time work rates are calculated as the number of workers using short-time work in a given month divided by the employment level in June 2019. The figure displays the 95% confidence intervals with the main estimate.

Unemployment rate: Lastly, Figure A1 in the appendix shows that the working from home potential of regions did not impact their unemployment rates in 2020, similarly to what we find for the effect of digital capital. While we find significant differences in early 2021, these differences are economically marginal, as they are lower than 0.2 percentage points between regions with a one standard deviation difference in WfH potential.

5.3 The complementarity of digital capital and working from home

We have shown that both digital capital and working from home reduced the short-time work rate during the pandemic. In fact, digital capital and working from home are likely complementary. Efficient remote work requires good digital equipment (laptops, adequate software and VPN connections, etc.), while the necessity to work remotely during the first months of the crisis made digital capital even more valuable. To substantiate this hypothesis, we conduct two exercises. First, we show that pre-pandemic digital capital predicts actual working from home usage during the pandemic. Second, we include our measures of digital capital and working from home potential in the same specification.

In the first exercise, we show that local exposure to digital capital increased the share of individuals actually working remotely in early 2021, as depicted in the left panel of Figure

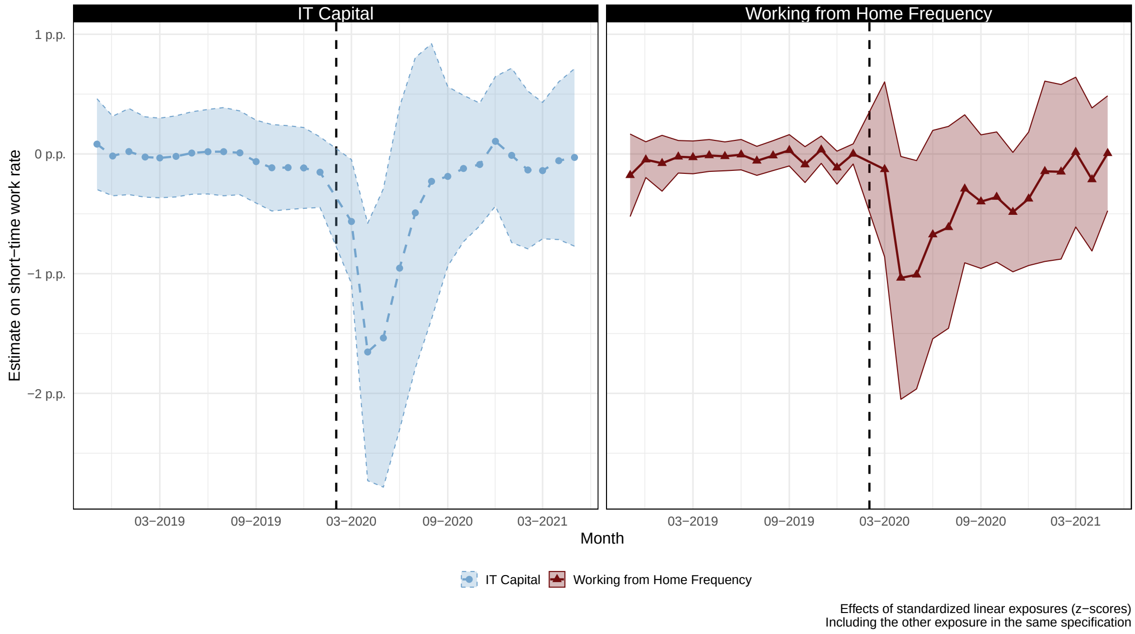
A2. The correlation between local digital capital per worker and actual WfH adoption is even stronger in the subset of local labour markets with a significant share of jobs that could be done remotely, as shown in the right panel of Figure A2. This suggests that digital capital endowment was necessary for individuals to effectively work remotely. In other words, even if a job could be done from home, the lack of appropriate digital tools prevented individuals from adopting remote work arrangements.

In the second exercise, we add the measures of digital capital and working from home in the same event study specification. Given that we need to use a different weighting scheme to analyse the impact of digital capital and working from home potential, we cannot analyse complementarities using a standard interaction term. We thus first simply add the measure of working from home in the event study specification for digital capital to analyse how the estimated coefficients differ compared to the results of Figure 4. This is shown in the left panel of Figure 6, which is very similar to the main specification. Thus the impact of digital capital does not seem to be driven by working from home. We then add the measure of digital capital in the event study specification for working from home. The right panel of Figure 6 shows that estimated impact of working form home potential appears to be smaller than in Figure 5. The estimate for April and May 2020 is of 1 pp compared to 1.5 pp in the previous specification and it is not statistically significant afterwards. This suggests that at least part of the negative impact of working from home on short-time work is due to a higher digital capital endowment and thus provides some support of the complementarity of digital capital and working from home.

6 Discussion

We find that digital capital, as measured by local labour markets' exposure to information and communication technologies, mitigated the adverse effects of the pandemic on local labour markets. Some channels through which digital capital played a role were specific to the COVID-19 shock, such as the need to work from home at the onset of the pandemic. Moreover, remote work and digital communication reduced the need for physical contacts and thus the risk of virus transmission within firms, enabling them to more effectively minimise sick leave and maintain production. We do indeed find that working from home led to a lower short-time work rate. But this was especially the case during the first months of the pandemic when strong contact restrictions were in place. Digital capital had a larger and longer-lasting effect on employment than working from home potential, particularly at the bottom of the regional distribution, which can be seen by comparing the effect of digital capital in Table 1 and working from home and Table 3. Moreover, the effect of digital capital remains large and significant even after controlling for

Figure 6: Including digital capital and working from home potential in the same specification



NOTE.- The estimates measure the change in short-time work rates relative to February 2020 for a standard deviation increase in digital capital potential (left panel) or in working from home potential (right panel). The two panels report results from different specifications using weights that are specific to digital capital potential in the left panel and to working from home potential in the right panel. Digital capital and working from home potential are included in both specifications. Short-time work rates are calculated as the number of workers using short-time work in a given month divided by the employment level in June 2019. The figure displays the 95% confidence intervals.

working from home potential in the same regression. This suggests that digital capital played a substantial role in enhancing labour market resilience during the crisis, even beyond facilitating remote work. The effect of digital capital on short-time work disappears only when labour markets recover from the shock in the summer 2021 with short-time work rates falling below 5% on average and the unemployment rate reaching similar levels than before the pandemic.

Other channels are more general and broadly linked to the impact of ICT on productivity, mainly by enabling more rapid sharing of information and improving decision-making strategies within firms.[11] Indeed, the pandemic amplified the importance of ICT in firm organisation and strategic decisions, such as in swiftly countering supply chain interruptions. At the local level, there may be also important benefits of a more intensive use of ICT and higher profitability of other businesses due to general equilibrium effects such as the lack of negative supply and demand spillovers Oikonomou et al. (2023) or due to better business services such as more efficient credit provision by the banking industry Pierri and Timmer (2022). The fact that we find a moderate impact of ICT capital even in periods were strict lockdowns were not in place (see Table 1) suggests that some of these channels that are not specific to the Covid-19 pandemic

[11]See for example Vu et al. (2020) for a recent review of the literature on ICT and economic growth.

may have been important as well.

Next, we discuss potential reasons that may explain why the impact of the pre-pandemic digital capital potential was significantly less pronounced in early 2021 compared to 2020, despite a second lockdown. Through this discussion, we identify avenues for future research. First, digital capital potential was an important determinant of the evolution of short-time work rates at the worst of the crisis, when disruptions were major. It lost its predictive power with the relaxation of social distancing rules. Second, the limited persistence in the effect of pre-crisis digital capital on short-time work may be due to the changes in the distribution of digital capital across regions during the pandemic, through which regions lagging behind at the start would have caught up to the others by the end of 2020. The dynamic of digital capital adoption during the pandemic is an important aspect that we cannot study with current data at hand. Data on digital capital at the regional level, or on both the industry and regional levels, would be useful to provide a picture of actual digital capital differences across regions and to explore further questions related to the implications of the spatial digital divide. Regional data on digital capital would be particularly useful to study the regional convergence in digital capital endowment during the pandemic through investments in digital technologies.

Indeed, firms have increased the adoption of ICT because of the pandemic (Bellmann et al., 2021). However, the evidence so far goes in the direction of a widening of the digital divide between firms. Gathmann et al. (2023) show that two-thirds of German firms simultaneously invested in ICTs and on-the-job training during the pandemic. Adopting firms are more likely to be large, high-skill, high-wage firms; and the ICT adoption benefited skilled men the most. Barth et al. (2022) also find that the most productive firms invested faster in new technologies in Norway. In fact, Rückert et al. (2020) document a widening digital divide across firms in Europe and the US that correlates with firms' differences in innovation, employment and profits. Overall, there is still little firm-level evidence on digital investments during and after the pandemic. Insights on whether digital investments made firms more resilient to the crisis would be valuable. Turning to the regional divide, how the dispersion in firms' adjustments will affect spatial inequality in the long term remains an open question for future research.

To complement studies on the evolution of the digital divide across firms, it would also be important to gain insights into how the digital skills of the labour force have evolved with the pandemic. While we did not find evidence of ICT skills influencing the role of digital capital for local labour market resilience on average, ICT skills have been found to influence individuals earnings and may be linked to within-region inequality. With the ongoing adoption of digital technologies and remote work practices, the question of whether individuals with lower levels of digital competency could catch up in terms of ICT skills has long-term consequences for spatial inequality.

Finally, regional differences in digitalisation have not led to a persistent widening of regional inequalities in (un)employment. First, the extensive and generous aid policies that prevented firm destruction and supported worker retention at the worst of crisis are a likely reason behind the short-lived effect of digital capital potential on labour markets. The likely positive effect of short-time work schemes in avoiding persistent labour market consequences is consistent with the literature on short-time work as an effective tool to reduce layoffs against large temporary shocks (Giupponi et al., 2022; Kopp and Siegenthaler, 2021; Giupponi and Landais, 2022). Second, the rapid recovery of regional labour markets across Germany was also likely explained by a high rate of successful job transitions out of occupations that were hit hard in this period. Indeed, job mobility increased significantly in 2020 among employees originally working in jobs registering the highest drop in vacancies, in particular in the hospitality sector (Arntz et al., 2023a).

7 Conclusion

This article examines the impact of digitalisation and working from home on how local labour markets in Germany responded to the pandemic-induced shock over an extended period. While the share of employees in short-time work spiked to 18% at the beginning of the pandemic, local labour markets experienced a very different increase in short-time work rates with differences exceeding 30 percentage points. Regional differences attenuated over time while the national short-time work rate fell below 5% a year and half after the shock.

Our analysis delves into the influence of pre-crisis levels of digitalisation on the varying regional effects, using metrics related to the potential for adopting digital technology and the ability to work from home. For the digital capital potential of a region we weigh industry-level digital capital by the region's industry employment shares just before the shock and use similarly computed potentials for working from home.

To identify the effect of digitalisation on the resilience of labour markets, we first adopt a difference-in-differences strategy for continuous treatment. We find that a higher digital capital potential before the pandemic contributed to lower short-time work rates during the pandemic. The effect was especially large at the onset of the shock when the disruptions were major. A second empirical strategy using instrumental variables confirms this finding. A higher working from home potential also led to a reduced usage of short-time work schemes. However, we find a significant impact of digital capital potential also conditional on our working from home measure, suggesting that other channels mattered as well.

Interestingly, the effect of digital capital was non-linear and concentrated at the bottom of the distribution, where digital capital mattered for about a year and a half until labour markets recovered. Policies targeting better labour market resilience to an economic shock should therefore focus on regions that are lagging behind, thereby reducing the spatial digital divide.

In conclusion, our research underscores the pivotal role of digitalisation in bolstering the resilience of regional labour markets to economic shocks such as the pandemic. Future studies should further explore the evolution of the spatial digital divide post-crisis and its broader implications for economic inequality.

References

Abadie, Alberto (2005) "Semiparametric difference-in-differences estimators," *The Review of Economic Studies*, 72 (1), 1–19.

Adams-Prassl, Abi, Teodora Boneva, Marta Golin, and Christopher Rauh (2020) "Inequality in the impact of the coronavirus shock: Evidence from real time surveys," *Journal of Public Economics*, 189 (1), 104245.

——— (2022) "Work that can be done from home: Evidence on variation within and across occupations and industries," *Labour Economics*, 74, 102083.

Alipour, Jean-Victor, Harald Fadinger, and Jan Schymik (2021) "My home is my castle - The benefits of working from home during a pandemic crisis," *Journal of Public Economics*, 196, 104373.

Alipour, Jean-Victor, Oliver Falck, and Simone Schüller (2023) "Germany's capacity to work from home," *European Economic Review*, 151, 104354.

Alon, Titan, Sena Coskun, Matthias Doepke, David Koll, and Michèle Tertilt (2022) "From mancession to shecession: Women's employment in regular and pandemic recessions," *NBER Macroeconomics Annual*, 36 (1), 83–151.

Arntz, Melanie, Sarra Ben Yahmed, Eduard Brüll, and Michael Stops (2023a) "Till a Shutdown Do Us Part : The Covid-19-Shock to Local Labour Demand, Occupational Mobility and its Long-Term Impact," mimeo, ZEW Mannheim.

Arntz, Melanie, Michael Böhm, Georg Graetz, Terry Gregory, Jan Moritz Johanning, Florian Lehmer, Cäcilia Lipowski, Britta Matthes, and Nick Niers (2023b) "Digitalisierung in der Covid-19-Pandemie: Corona hat den digitalen Graben zwischen den Betrieben vertieft.,"Technical report, IAB - Institute for Employment Research.

Aum, Sangmin, Sang Yoon Lee, and Yongseok Shin (2021) "COVID-19 doesn't need lockdowns to destroy jobs: The effect of local outbreaks in Korea," *Labour Economics*, 70, 101993.

Autor, David H. and David Dorn (2013) "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market," *American Economic Review*, 103 (5), 1553–97, 10.1257/aer.103.5.1553.

Autor, David H, Frank Levy, and Richard J Murnane (2003) "The skill content of recent technological change: An empirical exploration," *The Quarterly journal of economics*, 118 (4), 1279–1333.

Bai, John (Jianqiu), Erik Brynjolfsson, Wang Jin, Sebastian Steffen, and Chi Wan (2021) "Digital Resilience: How Work-From-Home Feasibility Affects Firm Performance," Working Paper 28588, National Bureau of Economic Research, 10.3386/w28588.

Barrero, Jose Maria, Nicholas Bloom, and Steven J Davis (2021) "Why Working from Home Will Stick," Working Paper 28731, National Bureau of Economic Research, 10.3386/w28731.

Barth, Erling, Alex Bryson, and Harald Dale-Olsen (2022) "Creative Disruption: Technology Innovation, Labour Demand and the Pandemic,"Technical report, IZA Institute for Labour Economics.

Bauer, Anja and Enzo Weber (2020) “COVID-19: How much unemployment was caused by the shutdown in Germany?” *Applied Economics Letters*, 1–6.

Béland, Louis-Philippe, Abel Brodeur, and Taylor Wright (2023) “The short-term economic consequences of Covid-19: Exposure to disease, remote work and government response,” *PLOS ONE*, 18 (3), e0270341.

Bellmann, Lutz, Pauline Bourgeon, Christina Gathmann, Christian Kagerl, David Marguerit, Ludivine Martin, Laura Pohlan, and Duncan Roth (2021) “Digitalisierungsschub in Firmen während der Corona-Pandemie,” *Wirtschaftsdienst*, 101 (9), 713–718.

Berger, David, Nicholas Turner, and Eric Zwick (2020) “Stimulating Housing Markets,” *The Journal of Finance*, 75 (1), 277–321.

Bertschek, Irene, Michael Polder, and Patrick Schulte (2019) “ICT and resilience in times of crisis: evidence from cross-country micro moments data,” *Economics of Innovation and New Technology*, 28 (8), 759–774.

Bluedorn, John, Francesca Caselli, Niels-Jakob Hansen, Ippei Shibata, and Marina M Tavares (2023) “Gender and employment in the COVID-19 recession: Cross-country evidence on “she-cessions”,” *Labour Economics*, 81, 102308.

Bontadini, Filippo, Carol Corrado, Jonathan Haskel, Massimiliano Iommi, and Cecilia Jona-Lasinio (2023) “EUKLEMS & INTANProd: industry productivity accounts with intangibles,”Technical report, Rome: LUISS Lab of European Economics.

Burda, Michael C and Jennifer Hunt (2011) “What explains the German labor market miracle in the Great Recession?”Technical report, National Bureau of Economic Research.

Callaway, Brantly, Andrew Goodman-Bacon, and Pedro HC Sant’Anna (2021) “Difference-in-Differences with a Continuous Treatment,”Technical report, arXiv preprint arXiv:2107.02637.

Card, David (1992) “Using regional variation in wages to measure the effects of the federal minimum wage,” *ILR Review*, 46 (1), 22–37.

Chiou, Lesley and Catherine Tucker (2020) “Social distancing, internet access and inequality,”Technical report, National Bureau of Economic Research.

Comin, Diego A, Marcio Cruz, Xavier Cirera, Kyung Min Lee, and Jesica Torres (2022) “Technology and Resilience,” Working Paper No. 29644, National Bureau of Economic Research.

Crescenzi, Riccardo, Mara Giua, and Davide Rigo (2022) “How many jobs can be done at home? Not as many as you think!,” Discussion Paper No. 37, Department of Geography and Environment, LSE.

Doerr, S., M. Erdem, G. Franco, L. Gambacorta, and A. Illes (2021) “Technological capacity and firms’ recovery from Covid-19,” *Economics Letters*, 209, 110102.

Fong, Christian, Chad Hazlett, and Kosuke Imai (2018) “Covariate balancing propensity score for a continuous treatment: Application to the efficacy of political advertisements,” *The Annals of Applied Statistics*, 12 (1), 156 – 177.

Forman, Chris, Avi Goldfarb, and Shane Greenstein (2012) “The Internet and local wages: A puzzle,” *American Economic Review*, 102 (1), 556–75.

Forsythe, Eliza, Lisa Kahn, Fabian Lange, and David Wiczer (2020) "Labor demand in the time of COVID-19: Evidence from vacancy postings and UI claims," *Journal of Public Economics*, 189, 104238.

Frodermann, Corinna, Philipp Grunau, Georg-Christoph Haas, and Dana Müller (2021) "Homeoffice in Zeiten von Corona: Nutzung, Hindernisse und Zukunftswünsche,"Technical report, IAB - Institute for Employment Research.

Furceri, Davide, Prakash Loungani, Jonathan D Ostry, and Pietro Pizzuto (2022) "Will COVID-19 have long-lasting effects on inequality? Evidence from past pandemics," *The Journal of Economic Inequality*, 20 (4), 811–839.

Gal, Peter, Giuseppe Nicoletti, Theodore Renault, Stéphane Sorbe, and Christina Timiliotis (2019) "Digitalisation and productivity: In search of the holy grail–Firm-level empirical evidence from EU countries," *OECD Economics Department Working Papers, No. 1533.*

Gathmann, Christina, Christian Kagerl, Laura Pohlan, and Duncan Roth (2023) "The Pandemic Push: Digital Technologies and Workforce Adjustments,"Technical report, IZA Institute for Labour Economics.

Giupponi, Giulia and Camille Landais (2022) "Subsidizing Labour Hoarding in Recessions: The Employment and Welfare Effects of Short-time Work," *The Review of Economic Studies*, 90 (4), 1963–2005.

Giupponi, Giulia, Camille Landais, and Alice Lapeyre (2022) "Should We Insure Workers or Jobs During Recessions?" *Journal of Economic Perspectives*, 36 (2), 29–54.

Greifer, Noah (2021) *WeightIt: Weighting for Covariate Balance in Observational Studies*, `https://CRAN.R-project.org/package=WeightIt`, R package version 0.12.0.

Hamann, Silke, Annekatrin Niebuhr, Duncan Roth, and Georg Sieglen (2023) "How does the COVID-19 pandemic affect regional labour markets and why do large cities suffer most?"Technical report, IAB - Institute for Employment Research.

Hershbein, Brad and Harry J. Holzer (2021) "The COVID-19 Pandemic's Evolving Impacts on the Labor Market: Who's Been Hurt and What We Should Do,"Technical report, IZA Institute for Labour Economics.

Hershbein, Brad and Lisa B. Kahn (2018) "Do Recessions Accelerate Routine-Biased Technological Change? Evidence from Vacancy Postings," *American Economic Review*, 108 (7), 1737–1772, 10.1257/aer.20161570.

Hershbein, Brad and Bryan A. Stuart (2023) "The Evolution of Local Labor Markets after Recessions,"Technical report, IZA Institute for Labour Economics.

Herzog-Stein, Alexander, Patrick Nüß, Lennert Peede, and Ulrike Stein (2021) "Germany's Labour Market in Coronavirus Distress - New Challenges to Safeguarding Employment," GLO Discussion Paper 840, Global Labor Organization (GLO), Essen.

Imai, Kosuke and Marc Ratkovic (2014) "Covariate balancing propensity score," *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 76 (1), 243–263.

Irlacher, Michael and Michael Koch (2021) "Working from home, wages, and regional inequality in the light of COVID-19," *Jahrbücher für Nationalökonomie und Statistik*, 241 (3), 373–404.

Kong, Edward and Daniel Prinz (2020) "Disentangling policy effects using proxy data: Which shutdown policies affected unemployment during the COVID-19 pandemic?" *Journal of Public Economics*, 189, 104257.

Kopp, Daniel and Michael Siegenthaler (2021) "Short-Time Work and Unemployment in and after the Great Recession," *Journal of the European Economic Association*, 19 (4), 2283–2321.

Kropp, Per and Barbara Schwengler (2016) "Three-Step Method for Delineating Functional Labour Market Regions," *Regional Studies*, 50 (3), 429–445.

Lemieux, Thomas, Kevin Milligan, Tammy Schirle, and Mikal Skuterud (2020) "Initial impacts of the COVID-19 pandemic on the Canadian labour market," *Canadian Public Policy*, 46 (S1), S55–S65.

Ma, Chang, John H. Rogers, and Sili Zhou (2020) "Global Economic and Financial Effects of 21st Century Pandemics and Epidemics," *Covid Economics* (5), 56–78.

Mian, Atif and Amir Sufi (2012) "The Effects of Fiscal Stimulus: Evidence from the 2009 Cash for Clunkers Program," *The Quarterly Journal of Economics*, 127 (3), 1107–1142.

Munch, J, Morten Olsen, Valerie Smeets, and Frederic Warzynski (2018) "Technological Change and Its Implications for the Labor Market, Productivity and the Nature of Work,"Technical report, Mimeo.

Oikonomou, Myrto, Nicola Pierri, and Yannick Timmer (2023) "IT Shields: Technology Adoption and Economic Resilience during the COVID-19 Pandemic," *Labour Economics*, 102330.

Pierri, Nicola and Yannick Timmer (2022) "The importance of technology in banking during a crisis," *Journal of Monetary Economics*, 128, 88–104.

Reveiu, Adriana, Maria Denisa Vasilescu, and Alexandru Banica (2023) "Digital divide across the European Union and labour market resilience," *Regional Studies*, 57 (12), 2391–2405, 10.1080/00343404.2022.2044465.

Rohrbach-Schmidt, Daniela and Anja Hall (2020) *BIBB/BAuA employment survey 2018*: Bundesinstitut für Berufsbildung.

Rückert, Désirée, Reinhilde Veugelers, and Christoph Weiss (2020) *The growing digital divide in Europe and the United States* (2020/07): EIB Working Papers.

Stawarz, Nico, Matthias Rosenbaum-Feldbrügge, Nikola Sander, Harun Sulak, and Vanessa Knobloch (2022) "The impact of the COVID-19 pandemic on internal migration in Germany: A descriptive analysis," *Population, Space and Place*, 28 (6), e2566.

Valero, Anna, Capucine Riom, and Juliana Oliveira-Cunha (2021) "The Business Response to Covid-19 One Year On: Findings from the Second Wave of the CEP-CBI Survey on Technology Adoption," CEP COVID-19 Analysis No. 024, Centre for Economic Performance, London School of Economics and Political Science, Houghton Street, London, WC2A 2AE, UK.

Vu, Khuong, Payam Hanafizadeh, and Erik Bohlin (2020) "ICT as a driver of economic growth: A survey of the literature and directions for future research," *Telecommunications Policy*, 44 (2), 101922.

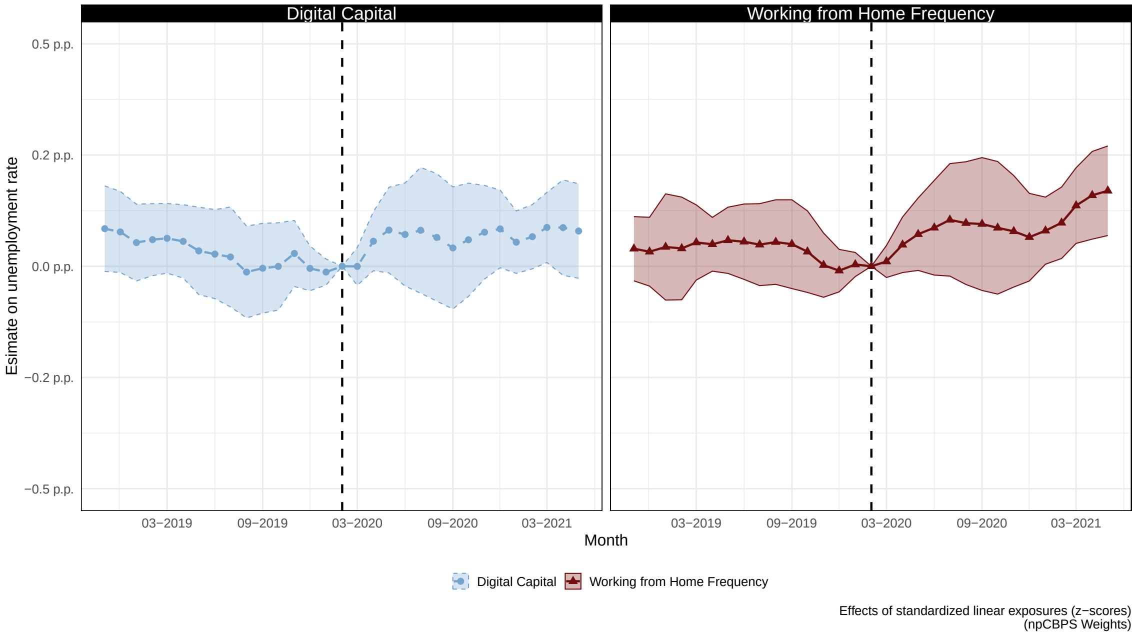
Wang, Zhi, Shang-Jin Wei, Xinding Yu, and Kunfu Zhu (2022) "Global value chains over business cycles," *Journal of International Money and Finance*, 126, 102643.

Yagan, Danny (2019) "Employment Hysteresis from the Great Recession," *Journal of Political Economy*, 127 (5), 2505–2558, 10.1086/701809.

Appendix

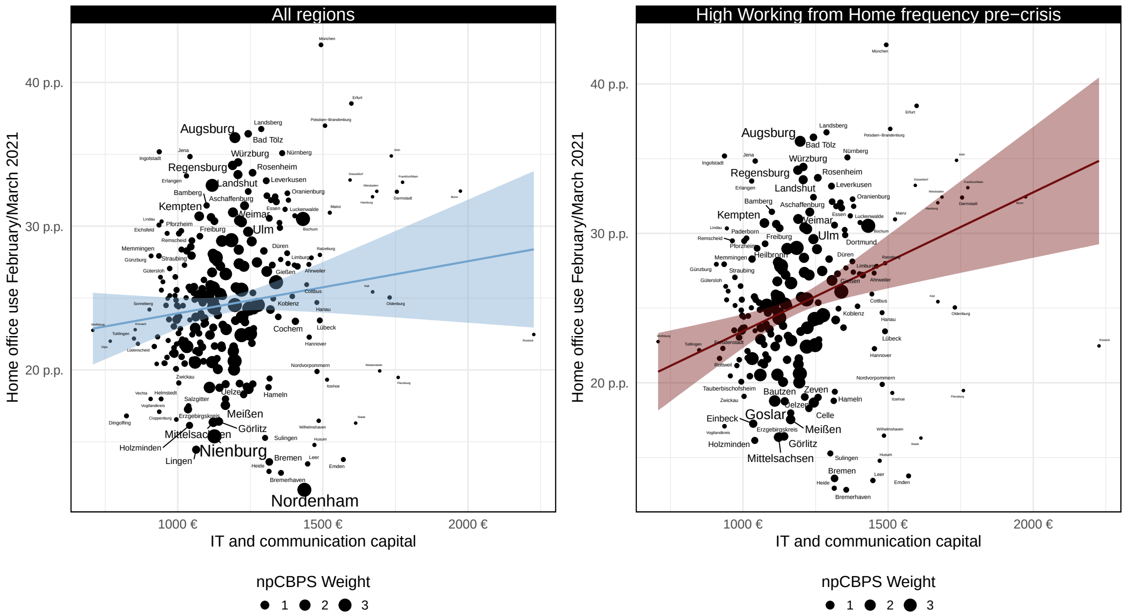
A Other results

Figure A1: Event study estimates on unemployment rates



NOTE.- The figure reports the change in unemployment rates for a standard deviation increase in ICT capital (left panel) or working from home potential (right panel). Unemployment rates are calculated as the number of unemployed individuals in a given month over the employment level in June 2019. The npCBPS weight of observations is represented by the size of dots/triangles.

Figure A2: Actual Post-crisis Working from Home Usage and Pre-crisis Digital Capital



NOTE.- The figure reports the share of individuals regularly working from home in labour market regions ordered by their level of digital capital per worker. The left panel with a blue line shows the correlation for all local labour markets. The right panel with a red line shows the correlation between digital capital and actual WfH in local labour markets with a high pe-crisis WfH potential, i.e. a high share of jobs that can be done from home according to pre-crisis occupational structure. Data on actual usage of remote work in March 2021 comes from the Federal Employment Agency.

B Data and Descriptive statistics

Table B.1: List of industries with information on ICT capital from EU Klems database

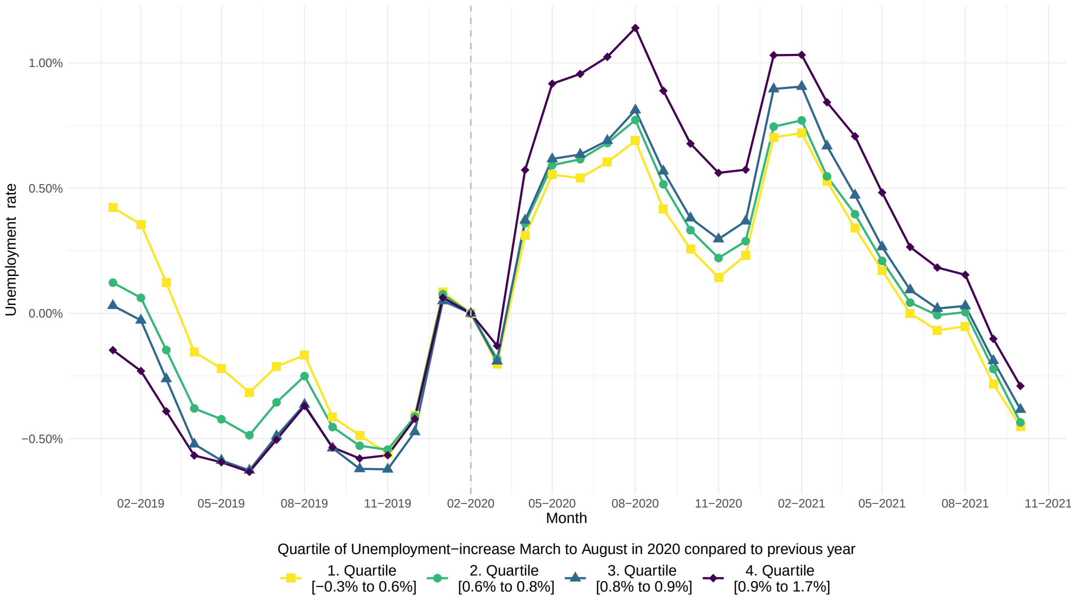
1	Agriculture, forestry and fishing
2	Mining and quarrying
3	Food products, beverages and tobacco
4	Textiles, wearing apparel, leather and related products
5	Wood and paper products
6	Coke and refined petroleum products
7	Chemicals and chemical products
8	Basic pharmaceutical products and pharmaceutical preparations
9	Rubber and plastics products, and other non-metallic mineral products
10	Basic metals and fabricated metal products, except machinery and equipment
11	Computer, electronic and optical products
12	Electrical equipment
13	Machinery and equipment n.e.c.
14	Transport equipment
15	Other manufacturing
16	Electricity, gas, steam and air conditioning supply
17	Water supply; Waste
18	Construction
19	Wholesale and retail trade and repair of motor vehicles and motorcycles
20	Retail trade, except of motor vehicles and motorcycles
21	Land transport and transport via pipelines
22	Water transport
23	Air transport
24	Warehousing and support activities for transportation
25	Postal and courier activities
26	Accommodation and food service activities
27	Publishing, audio-visual and broadcasting activities
28	Telecommunications
29	IT and other information services
30	Financial and insurance activities
31	Real estate activities
32	Professional, scientific, technical, administrative and support service activities
33	Public administration and defence
34	Education
35	Health and social work
36	Arts, entertainment and recreation
37	Other service activities
38	Activities of households as employers
39	Activities of extraterritorial organizations and bodies
40	Other service activities

Source.- EUKLEMS & INTANProd database.

Figure B.1 plots the regional unemployment rate by quartiles of the average regional increase in unemployment of the unemployment rate between March and August 2020 compared to the same months in 2019. Similarly to STW, unemployment also increased with the pandemic but by much smaller magnitude. The unemployment rate was the highest in August 2020 with regional increases ranging from 0.2 to 2.7 percentage points relative to August 2019.

The evolution of the unemployment rate followed the timing of the first two lockdowns but steadily decreased after the second one and was back to pre-crisis levels by summer 2021. While regional differences in the unemployment rate by the initial bite were high throughout 2020, by 2021 regional variation had reduced sharply.

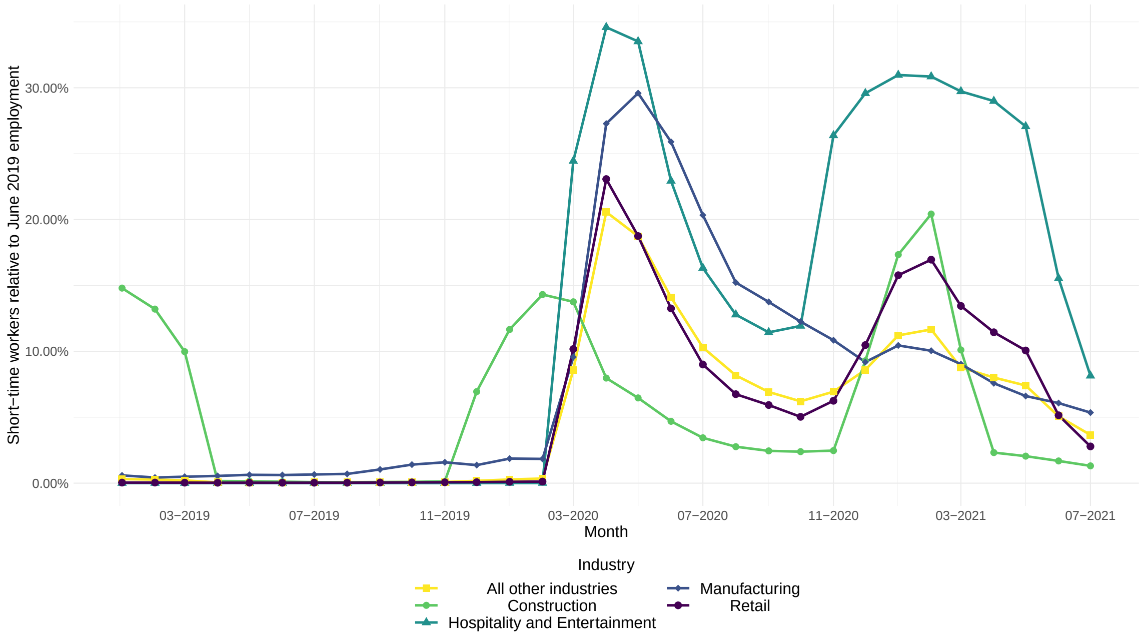
Figure B.1: Changes in unemployment across local labour markets



NOTE.- The figure shows the evolution of unemployment rates relative to February 2020 grouped by quartiles of the average increase of unemployment between March and August 2020 compared to the same time period in 2019.

The role of industry-composition in the evolution of short-time work across local labour markets The short-time work rate varied greatly across different sectors of the economy. Figure B.2 shows that the hospitality industry was affected the most with more than 30% of its pre-crisis workforce in short-time work during the first and second lockdown in summer and winter 2020. The manufacturing industry also had a pick in short-time work usage around 30% of its pre-crisis workforce in summer 2020 but showed then a steady decrease in its short-time work rate. The retail and other service industries registered short-time work rates around 20% in summer 2020 while only the retail industry was again more affected in winter.

Figure B.2: short-time work rates by industries



NOTE.- The figure shows the national industry-specific short-time work rates for 5 industries. This level of aggregation allows us to observe these same industries at the level of local labour markets. In contrast to our other results the figure shows the overall short-time work rate including seasonal short-time work while all other figures report business-cycle related short-time work.

To analyse, how the broad-industry employment composition of regions has affected, short-time work during the COVID crisis, we apply a decomposition of the deviation of the regional short-time work-rate from the national short-time work rate. This approach allows us to explore whether regional differences in short-time work are driven by regional differences in the sectoral mix of local labour markets or differences in short-time work rates within sectors. These within sector differences can be either due to within-sector differences in finer grained industry employment shares (i.e. short-time work rate differences in car manufacturing vs. paper manufacturing) or due to pure regional differences in short-time work rates in the same industries (i.e. higher short-time work rate in car manufacturing in a region A compared to a region B).

For the decomposition we, start out with the regional deviation of the short-time work rate from the national short-time work rate:

$$\textsc{Deviation}_r = \sum_r E_{ir} \times STW_{ir} - \sum_i E_i \times STW_i$$

where E_{ir} is the employment share of industry i in region r and STW_{ir} is the short-time work rate in industry i in region r. This deviation can be rewritten as a sum of two terms:

$$\textsc{Deviation}_r = \sum_i (E_{ir} - E_i) \times STW_i + \sum_i (STW_{ir} - STW_i) \times E_{ir}$$

The first term is a between-sector component that represents regional differences in employment composition across sectors:

$$\textsc{Composition}_r = \sum_i (E_{ir} - E_i) \times STW_i$$

If a region has a higher employment share in high short-time work sector (e.g. hospitality) than the national average this would be reflected in this component.

The second term captures the within-industry differences in short-time work response across regions:

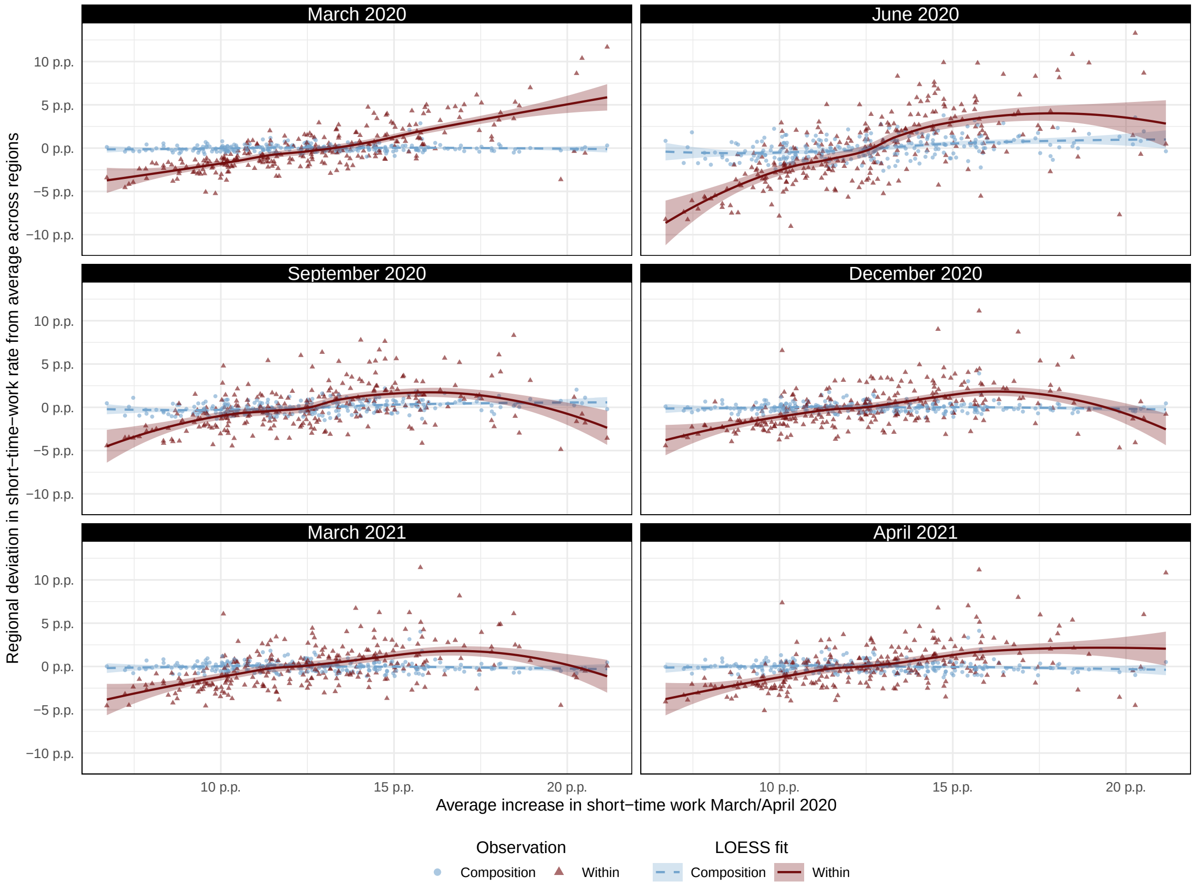
$$\textsc{Within}_r = \sum_i (STW_{ir} - STW_i) \times E_{ir}$$

This component captures whether regional differences exist due to higher short-time work rates in certain sectors compared to the national average. For example, if a region has a higher short-time work rate in manufacturing than the national average, this would be reflected in this component.

Figure B.3 displays the sector composition component and the within-sector component over time for regions ranked by their initial increase in short-time work rates. The within component, represented by the triangles and a thick line, explains almost all of the regional deviation in short-time work.

In the paper, we study how the digital capital exposure of regions influenced these regional differences in short-time work *within* these big industries. We do so by i) using information on local employment and on digital capital for more detailed industry groups (40 industries, including 13 manufacturing industries) and ii) controlling the for the local employment shares in the 1-digit manufacturing, construction, retail and hospitality industry.

Figure B.3: Decomposition of regional short-time work rates into industry-composition and within-industry components



NOTE.- The figure reports deviations in short-time work rates for each 257 labour market regions with respect to the average over all regions. Regions are ranked by their short-time work rates in March and April 2020. Short-time work rates are calculated as the number of workers using short-time work over the employment level in June 2019. For better readability two regions (Wolfsburg and Dingolfing) with extreme increases in short-time work in March 2020 that exceeded 25 p.p. were excluded.

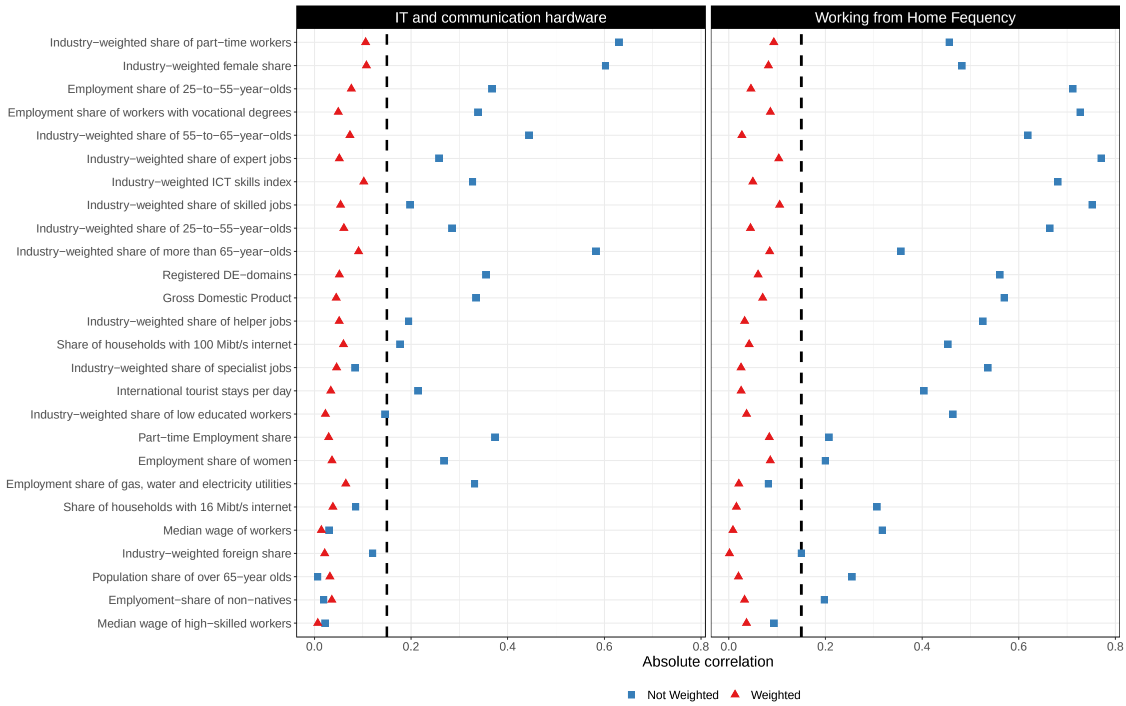
C Empirical strategy

Covariate balancing propensity score weighting We use the non-parametric covariate balancing generalised propensity score (npCBGPS) methodology by Fong et al. (2018). We compute the weights using the implementation in the WeightIT R-package by Greifer (2021). Adapting Imai and Ratkovic's 2014 covariate-balancing propensity score for continuous treatments, this method models assignment to a continuous treatment with a generalised propensity score, while also directly optimising covariate balance.

One advantage of this approach compared to maximum likelihood methods, is that no direct estimation of the generalised propensity score (GPS), and therefore also no correctly-specified functional form for the GPS, is needed. Instead the weights, i.e. $w_i = \frac{f(T_i)}{f(T_i|X_i)}$, are constructed without any parametric restrictions to the functional form of the generalised propensity score $f(T \mid X)$ or the marginal distribution of the treatment $f(T)$.

Weights are then chosen to maximise an empirical likelihood function subject to two constraints. First, as a stability condition the mean of the weights needs to be 1. Secondly, the weighted-sample correlations of X and T are restricted to allow for a maximum level of imbalance. However, this maximum value is not set to zero to simplify finding a solution for the optimisation problem. This is especially important if the covariates X predict T very well, which could otherwise result in extreme weights. To further alleviate the problem of extreme weights, we trim the weights at 5% and 95% to ensure that the effective sample size remains large.

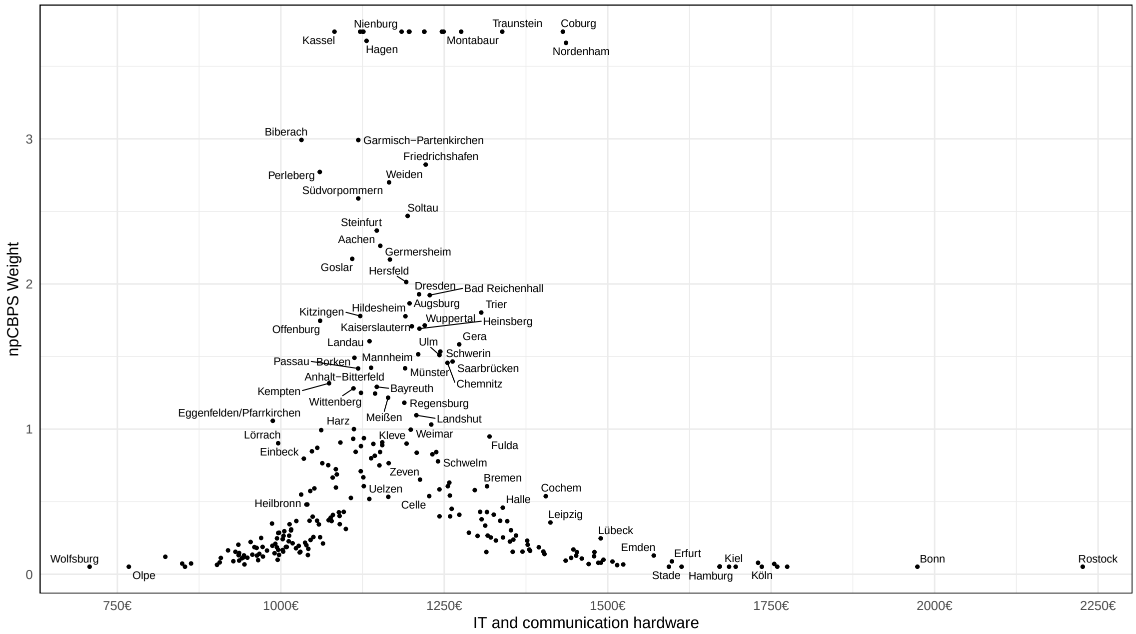
Figure C.1: Balance for non-targeted covariates



NOTE.- The figure shows the absolute correlations between both trageted and non-targeted covariates in our npCBPS weighting procedure and the measure for exposure to digital capital both in the unweighted (blue squares) and the weighted sample (red triangles) for both Digital Capital and the Working from Home Frequency.

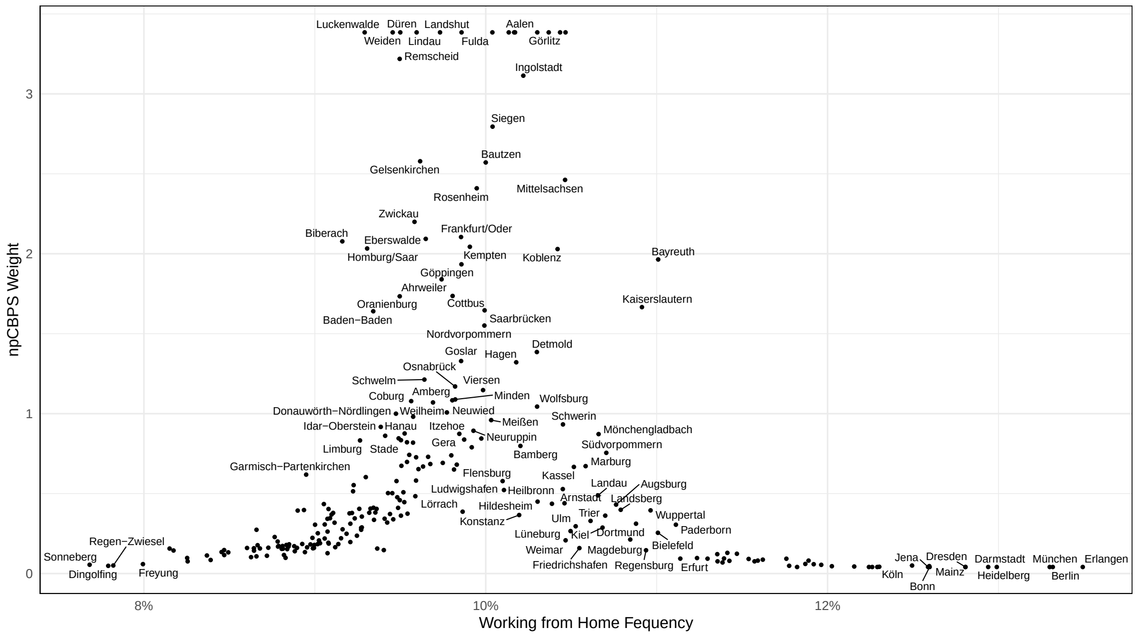
Figure C.2 gauges the common support assumption by showing the distribution of regional weights for the regression using digital capital. There are no extreme weights. The minimum weight is 0.0746 , while the maximum weight is 3.0333. The weights tend to be smaller for regions that have very high (e.g. Bonn) or very low digital capital (.e.g. Olpe) per worker compared to the average region. Overall, the distribution of the weights is left-skewed, with many low digital capital regions having weights higher than 0.25, while large urban high digital capital regions (exceeding €1500 per worker) tend to be a worse comparison group. Figure C.3 gauges the common support assumption for the regression using WfH potential.

Figure C.2: Weight distribution for regressions with local digital capital



NOTE.- The figure presents the npCBPS weights of regions along their digital capital distribution.

Figure C.3: Weight distribution for regressions with the Working from Home Potential



NOTE.- The figure presents the npCBPS weights of regions along the regional working- from-home potential distribution.