

Adjustments of Local Labour Markets to the COVID-19 Crisis: the Role of Digitalisation and Working-from-Home *

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Abstract

Employment responses to the COVID-19 crisis differed widely across German local labour markets, especially at the beginning of the pandemic, with differences in short-time work rates of up to 20 percentage points. In this paper, we show that digital capital, and to a lesser extent working-from-home, were important factors for the resilience of local labour markets. Using an empirical strategy that combines a difference-in-differences approach with propensity score weighting, we find that local exposure to digital capital reduced short-time work usage by up to 4 percentage points and the effect lasted for about 8 months. Working-from-home potential also lowered short-time work rates by 1 to 2 percentage points in the first four months of the pandemic when a strict lockdown was in place. Differences in unemployment rates across local labour markets were at most 2 percentage points and did not depend on digital capital or working-from-home potential.

Keywords: COVID-19 crisis, Digitalisation, Employment, Information and communication technologies, Local labour markets, short-time work, Working-from-home.

JEL codes: J21, O3, R12, R23

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1 Introduction

Digitalisation has spurred productivity growth and transformed the nature of work over the past few decades.¹ It has also come to be seen as crucial for socioeconomic resilience to crises.² In particular during the COVID-19 pandemic, digital capital is likely to have played an important role in managing the sudden and unprecedented labour market downturn. 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. 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 and the adoption of digital capital during the crisis have varied across regions and firms (Forman et al., 2012; Bellmann et al., 2021).

At the same time, local labour markets have been hit unequally by the COVID-19 crisis. In Germany, a country that introduced flexible short-time work schemes, the increase and spatial differences in short-time work take-up were unusually high at the onset of the pandemic. The short-time work rate spiked to 18% in April 2020. Increases in short-time work rates varied widely across local labour markets ranging from 9 to almost 38 percentage points. At the same time, the unemployment rate was just below 6% at its peak in summer 2020, which represented an increase of 1.2 percentage points relative to summer 2019. Changes in unemployment rates also differed across regions by up to 2.5 percentage points.

In this paper, we explore how local employment responses evolved and how they have been affected by endowments in digital capital and working-from-home potential in Germany in 2020 and 2021. Previous recessions tended to exacerbate 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 for the very early phase of the pandemic. A peculiarity of the COVID-19 pandemic is the unique role that digital technologies have played. To the best of our knowledge, this paper is the first attempt to analyse the role of local digital capital in affecting local employment responses to the crisis. More precisely, we study local labour markets' responses in both short-time work and unemployment rates using detailed administrative data at the county and industry level, or country and occupation level, over more than a year. By using the first dataset available

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

²Digitalisation matters for resilience, i.e. a fast recovery from shocks, 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; Pierri and Timmer, 2020).

³See for example Yagan (2019); Hershbein and Kahn (2018); Hershbein and Stuart (2020).

for spatial analysis, we complement early papers on the impact of the COVID-19 pandemic on the labour market that used individual surveys and/or focused on the short-run effects of the pandemic. In particular, the paper complements earlier work by Alipour et al. (2021) on the role of working-from-home potential in the first two months of the pandemic by extending the time horizon and exploring how it interacts with digital capital endowments.

To analyse the role of digitalisation on local employment, we use a difference-in-differences approach with continuous treatment. The intensity of the treatment depends on a region's pre-crisis exposure to digital capital and working-from-home potential. To measure local exposure to digital capital, we use pre-crisis data on information and communications technologies (ICT) capital in German industries and weight it with local employment shares by detailed industries. To measure local exposure to working-from-home, we weight pre-crisis working-from-home frequency for detailed occupations by local employment shares across detailed occupations. 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 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, the participation in the global value chain, the contact intensity of the workforce.

We first show that German local labour markets had 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 and persistent. While the short-run employment responses to the COVID-19 pandemic and the regional differences were unprecedented, local labour markets have quickly converged to similar and lower short-time work rates and reached pre-crisis unemployment levels by the end of 2021.

We find that local exposure to digital capital before the start of the pandemic reduces short-time work usage in the first 8 months of the pandemic. Regions in the bottom quintile of the digital capital distribution had short-time work rates higher by 4 percentage points (ca. 20-25%) compared to the average over all regions in the spring 2020. Working-from-home potential is one channel for the effect of digital capital on short-time work. Regions in the bottom quintile of the working-from-home potential distribution had a 2 percentage point (ca. 10%) positive deviation in short-time work compared to the average over all regions at the start of the first lockdown. However, we find that it mattered only in the short run, and show that the effect lasts until July 2020. After the relaxation of the first lockdown restrictions, a region's working-from-home potential did not matter for its employment outcomes, even if remote work remained

a common practice. Moreover, the effect of working-from-home potential on short-time work usage is only observed for the group of regions with higher digital capital. Regions with a low level of digital capital had equally high short-time work rates, irrespective of their working-from-home potential. This highlights that digital capital was a necessary precondition to effectively make use of working-from-home at the beginning of the pandemic. We also find that digital capital enabled to save jobs in the short-run beyond its effect on the ability to work remotely. Indeed, exposure to digital capital reduced the usage of short-time work even in regions with a low share of jobs that may be performed remotely. Overall, the results imply that the spatial digital divide brought further employment inequalities with the pandemic but only in the short to medium run. The higher use of short-time work in local labour markets with low digital capital has likely prevented longer term effects.

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 and present the results in section 5. We discuss the findings in section 6. The last section concludes.

2 Literature review

2.1 Labour markets' responses to shocks

This paper contributes to the literature on the impact of the COVID-19 crisis on the labour market. Several studies have analysed the impact of the crisis on employment for different groups of the population and find that less-educated workers and women have been more affected (see, e.g., Adams-Prassl et al., 2020; Hershbein and Holzer, 2021; Lemieux et al., 2020). The 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., 2021). Non-pharmaceutical interventions (NPIs), 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 the major cause of the increase in unemployment in Germany (Bauer and Weber, 2020). However, the increase in unemployment has been relatively modest in Germany, while the crisis has led to a substantial increase in short-time work (Adams-Prassl et al., 2020). We show for the first time that both the short-time work and unemployment

responses varies 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 have been much larger in magnitudes, 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, 2018). 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 leads to a drop in local employment even in the absence of lockdown, such as in South Korea, but that the effect is 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 infections rates led to variation in unemployment rates in April 2020. Surprisingly, Forsythe et al. (2020) find that the reductions in job vacancies were uniform across the U.S., without notable differences across states with different timing in the spread of the pandemic or in the implementation of lockdown measures.

More generally, 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, 2020, 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., 2020; 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 on regional disparities of this crisis.

2.2 The role of digital technologies and remote work in recessions

Digital technologies has 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. (2022) provide evidence that different measures of digital development proved to be important for labour market resilience during the Great Recession .

Arguably, the role of ICT 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. ICT has helped companies to reorganise work arrangements and production processes more quickly or to increase online sales (Comin et al., 2022). Moreover, manufacturing firms that have automated processes before the crisis may face fewer safety issues due to a lower human contact and thus have less disruptions in production. In fact, there is early evidence from the US showing that in areas where firms adopted more ICT before the crisis the unemployment rate rose less in Spring 2020 (Pierri and Timmer, 2020).

A further important reason why technology mattered during the pandemic recession is that it allowed and 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 only 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., 2020). 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, Irlacher and Koch (2021) show that in Germany’s poorer regions workers were less likely to work from home before the COVID-19 crisis. Thus, there is the potential that the pandemic crisis could amplify regional disparities due to the different WfH feasibility (or teleworkability). Alipour et al. (2021) present evidence that German districts with a higher share of teleworkable jobs experienced fewer short-time work registrations and less SARS-CoV-2 cases in April and May 2020. In this paper we complement and extend their findings by studying how the impact changed over time (1 year after the pandemic outbreak), by analysing the heterogeneous responses along the regional distribution of the WfH potential and by investigating how local exposure to digital capital shapes its impact.

Whether tasks could 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 an adequate ICT support. Investing in these technologies and processes may require time and previous knowledge and experience. In facts, there is evidence that firms invested extensively in digital technologies after the pandemic outbreak, but that larger and more innovative firms have invested relatively more (Bellmann et al., 2021; Valero et al., 2021).

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 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 the labour markets of counties (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 digit and is rarely available at a more disaggregated level within counties for confidentiality reasons. This data permits to disentangle 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. To abstract from seasonal short-time work 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 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 linkages, similar industry structures, and should therefore respond similarly to the COVID-19 shock.

3.2 Employment responses over time across local labour markets

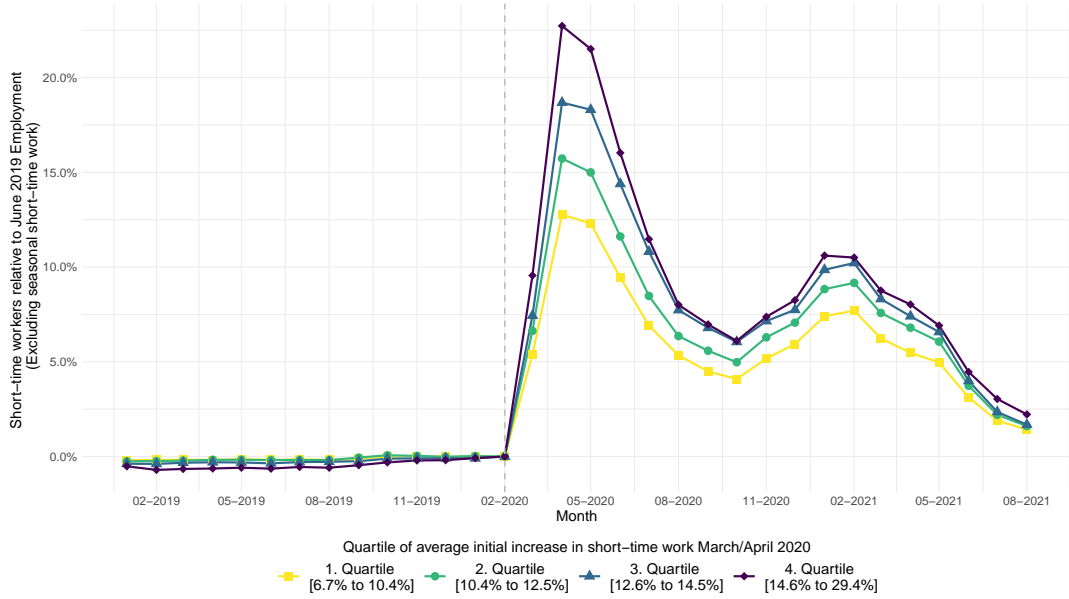
Local labour markets had different employment responses, especially at the onset of the pandemic. Figure 1 shows the evolution of short-time work usage over time for four groups of labour market regions ranked by their initial increase in short-time work rate. Short-time work rates saw sharp increases 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 reduced even further.

Figure 2 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. 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.

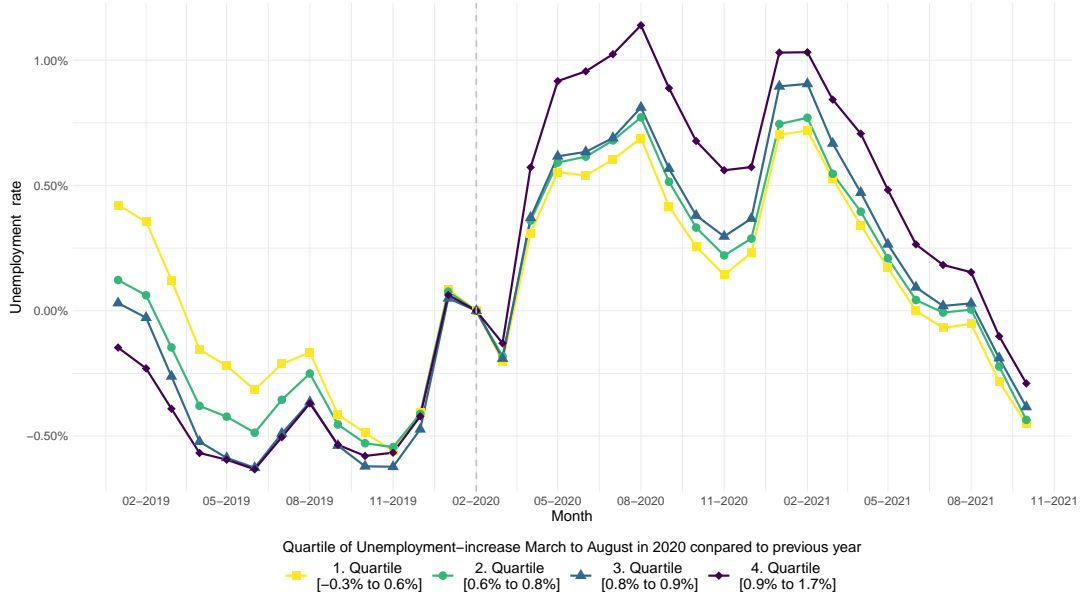
The effect of the crisis on employment varied greatly across sectors of the economy. The hospitality industry was affected the most. In the section B of the appendix, we compute a decomposition and show that regional differences in STW are mostly driven by differences in STW rates within 5 broad industries (construction, manufacturing, retail, hospitality, and other

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. 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.

Figure 2: 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.

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

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). The 2021-release of the EUKLEMS database provides data on the capital stock in different assets for 40 2-digit industries for Germany up until 2019.⁴ Our measure of ICT capital combines computing equipment capital and communications equipment capital. The industry classification is given in Table A1 in the appendix.

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 has been used just before the crisis. Alipour et al. (2020) compare the WfH potential constructed using information from the BIBB/BAuA Employment Survey to actual WfH take-up in 2020 and find that the measure is a good predictor of actual WfH use.

4 Empirical strategy

We describe here how we build the measures of local exposure to digitalisation, our empirical strategy to separate the effects of digitalisation during the COVID-19 crisis from other regional differences and the assumptions embedded in our approach.

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 exposure 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.⁵

⁴The data can be downloaded from the EUKLEMS & INTANProd website: <https://euklems-intanprod-lee.luiss.it/>

⁵The list of 40 industries is given in Table A1 in the appendix.

We construct a measure of regional potential digital capital per worker 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 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 :

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

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 managers quality. Our measure approximate the average potential for digital capital of a region given its industry structure and the national average digital capital of the industries. In other words, if an industry has a high digital capital in a region, it should be possible to invest as much in ICT in another region even if it is lagging behind.

There is a wide variation in the exposure to digital capital across German labour market regions that we can exploit. Figure 3 presents a map of the exposure to digital capital per worker. The average digital capital per worker in 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.

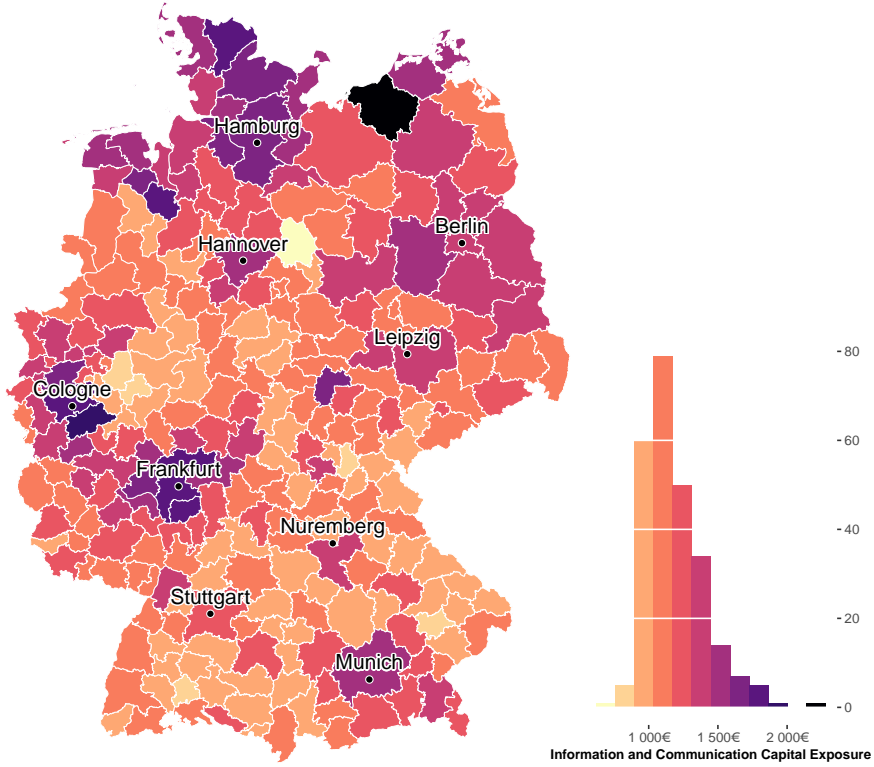
Working-from-home exposure The local exposure to WfH is based on data on actual working-from-home practices at the detailed occupation level in Germany before the pandemic. Similar to Alipour et al. (2020), we use data from the 2018 BIBB/BAuA Employment Survey and compute the average frequency of pre-crisis WfH for each 3-digit occupation. To compute the local exposure to WfH, we weight the occupation-specific WfH frequency with the local employment share of each occupation:

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

Figure 4 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.

Figure 3: Map of digital capital in labour market regions

Information and Communication Capital Exposure
Information and communication capital per worker in 2019



NOTE.- The map shows the local digital capital per capita as constructed as in equation 1 for all 257 labour market regions.

The regions with the highest exposure to WfH are Berlin, Munich and Erlangen, with jobs in which roughly 13.5% of workers reported to 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 regularly worked remotely before the pandemic.

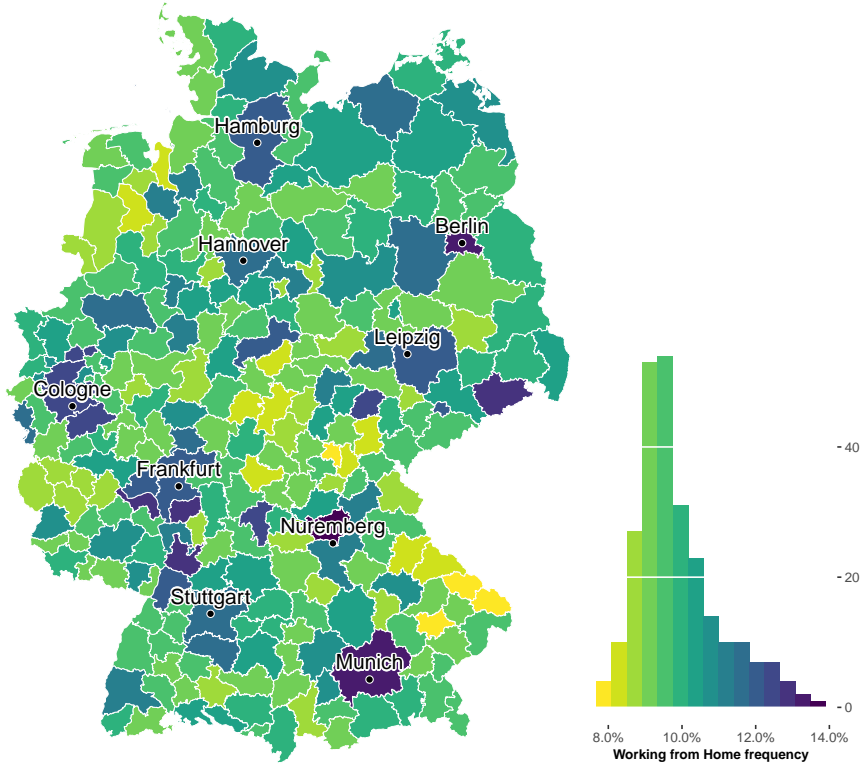
4.2 Difference-in-differences with a continuous treatment

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, a simple difference-in-differences design comparing treated and untreated regions over time is not suitable. Instead, we need to compare regions with different intensities of digitalisation and working-from-home potential and determine the impact of the Covid-19 shock for regions at different points of the digitalisation

Figure 4: Map of working-from-home potential

Working from Home frequency

Share of frequent/always teleworkers in pre-period



NOTE.- The map shows the average pre-crisis working-from-home frequency as constructed as in equation 2 for all 257 labour market regions.

distribution (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).

In our setting, the assumptions differ somewhat from the ones of a standard difference-in-differences design. Here, we summarise the assumptions we make, how we evaluate them and develop our empirical strategy based on a combination of a difference-in-differences strategy with a continuous exposure and non-parametric Covariate Balancing Propensity Score (npCBPS) weighting below. This strategy allows us to estimate the regional effects of our exposure variables on employment outcomes, while making regions more comparable through the weighting approach. In total, the strategy relies on four assumptions:

1. Strong parallel trends: Absent the covid crisis outcomes would have followed parallel trends along all levels of the continuous treatment. We address this assumption by showing pre-crisis exposure response profiles over time.

2. Conditional independence assumption: There should be no unobserved selection into specific levels of ICT capital. Conditionally on the covariates that are used to compute the weights, treatment levels should be as good as random.
3. Common support: We need this standard assumption to ensure that the generalized propensity score is non-zero for every treatment intensity and that the inverse propensity score weights do not become extreme. We address this assumption by trimming extreme weights and by plotting the distribution of weights across different treatment levels.
4. Stable unit treatment value assumption: Finally the level of digitization and telework in one region should not have employment effects on other regions during the crisis. For short-term analyses of employment responses, this assumption should be innocuous as large migration or capital transfers between regions would only happen over a longer time horizon.

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 crisis had not occurred.

An initial step for our design is to determine the relationship between the different levels of exposure and outcomes at different points in time. The aim here would be to approximate an exposure-response function for each relevant time period before and after the crisis and analyse how this function has changed over time. As a first validation exercise, we can estimate the exposure response function for the pre-crisis period and check whether there are (different) pre-trends for regions at all points of the exposure distribution.

To this end, we plot the outcome variables along the regional digitalisation exposure for different points in time, adding a LOESS estimation of the exposure response function. This allows us to compare how the exposure-response profile to digitalisation or teleworkability has changed over time and whether it stayed stable in the pre-crisis months. Moreover, we can use these plots to find appropriate event-study specifications which allow us to use a more aggregated and simpler representation of the main effects.

However, the issue of selection along specific exposure levels remains. Regions with different exposures to digitalisation and working-from-home potential likely differ in characteristics that are related to labour market resilience during the COVID crisis, such as the employment and education structure. These differences then lead to an attribution problem for the estimated exposure response effects. For example, if regions with a higher share of college-educated workers

also have a higher potential for home-based work, one needs to disentangle the impact of these two variables on labour market developments during the COVID crisis.

Covariate balancing propensity score weighting Thus, to solve this problem we utilise an inverse probability weighting strategy as a pre-processing step for our main analysis. This step allows us to approximate exposure response functions for a pseudo-population of regions where the relationship between local exposure variables and other observable characteristics is greatly reduced.

In particular, we compute regional weights based on the non-parametric covariate balancing generalised propensity score (npCBGPS) methodology by Fong et al. (2018).⁶ 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 $f(T | X)$ 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.

We apply separate weighting procedures for each treatment intensity but include the same covariates in both. First, we use information on the share of manufacturing jobs, the employment share of 1-digit industries, 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 crisis. Second, to account for the higher adaptability of high-skilled jobs we also include the share of college-educated workers in a region. Third, 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.⁷ Fourth, since firms and industries in some regions might be more used to the procedures related to

⁶We compute the weights using the implementation in the WeightIT R-package by Greifer (2021).

⁷We thank Moritz Meister and Annekatrin Niebuhr for sharing with us the data.

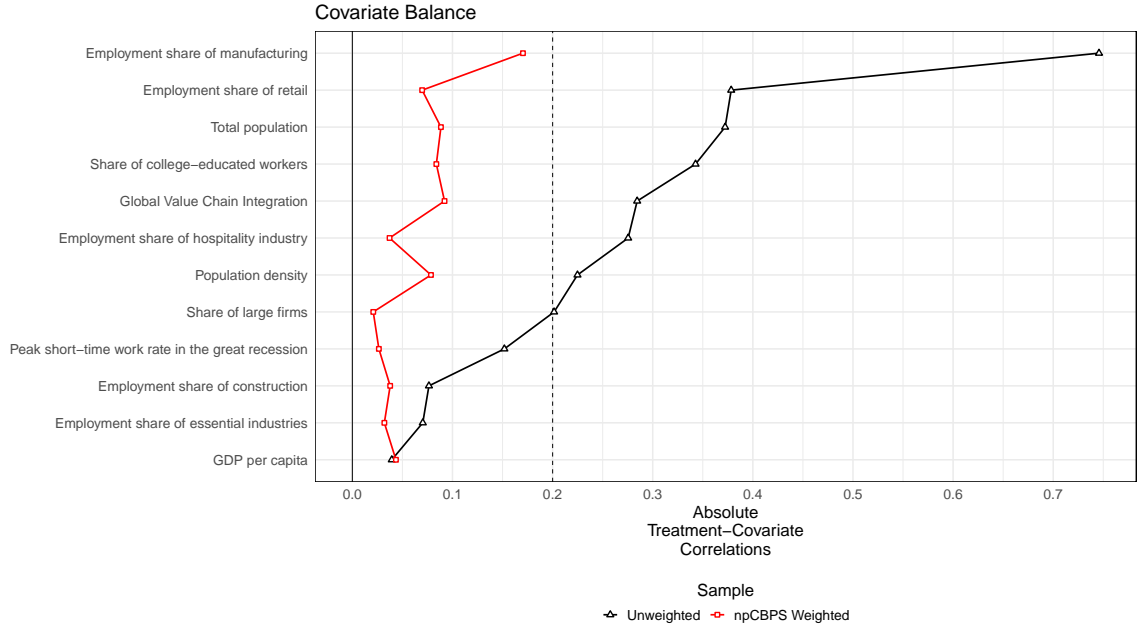
short-time work, we include the peak-short-time work rate during the Great recession in 2009 to address this issue. Fifth, since large firms are traditionally stronger users of short-time work, we include the share of firms with more than 250 employees. Lastly, in order to avoid comparisons across more and less agglomerated regions, we include population density, total population and the GDP per capita of regions into our set of covariates.

We present all our results first both with npCBPS pre-processing in the main text and without pre-processing in the appendix.

4.3 Validation of the weighting procedure

Comparability across regions with different ICT capital We first analyse how different pre-crisis endowments of ICT capital across regions have impacted their labour market performance during the COVID-19 crisis. Figure 3, in the previous section, shows that ICT capital tends to be concentrated in dense urban regions, which also differ along their demographic composition from the average German region. To create a pseudo-sample of comparable regions, we use a large set of regional characteristics and select the ones that enable us to minimise the correlation between regional ICT capital exposure and all regional characteristics using npCBPS weights. The set of covariates include several variables at the regional level that capture the demographic composition, the industry structure, the labour market structure, wealth and other aspects of digitalisation including Internet access and the number of registered ".de" domain names. The precise list of covariates can be seen on Figure C1 in the appendix.

Figure 5: Covariate Balance plot for regional ICT capital



NOTE.- The figure shows the absolute correlations between key covariates and the measure for exposure to digital capital both in the unweighted (black triangles) and the weighted sample (red squares).

Figure 5 shows that our weighting approach considerably improves the balance along key covariates. The black line indicates the absolute correlations of the variables we target in our reweighting procedure with the regional ICT capital exposure in the unweighted sample, while the red line reports the same correlations in the generated pseudo-sample after reweighting.

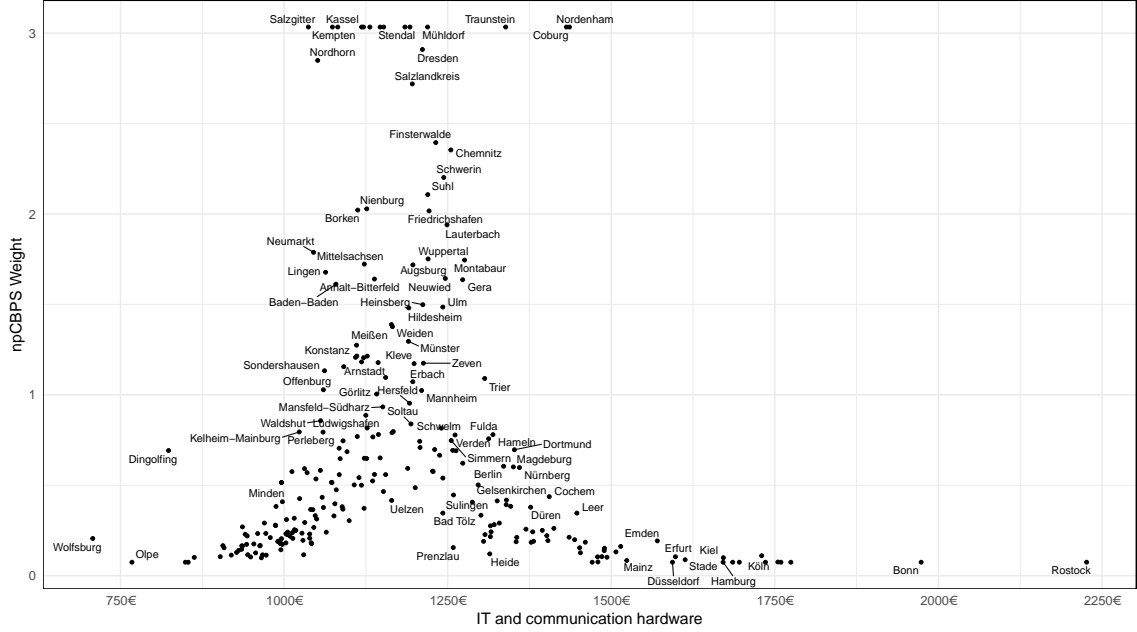
In the unweighted sample, the correlation between the share of manufacturing workers and local ICT capital is -0.746, making it almost impossible to isolate the effect of ICT capital from differences in the broad industry structure in a simple comparison of regions. Moreover, the education-structure of a region as well as the total population and population density are also highly correlated in the raw sample.

Conversely, none of these absolute correlations are larger than 0.17 in the weighted sample. The regions in the resulting pseudo-sample are comparable along all included weighting variables. Besides a strong improvement in the balance of the targeted characteristics, the weighting procedure also increase balance in several non-targeted dimensions as shown in Figure C1 in the appendix.

Common support Through weighting, the effective sample size is reduced from 257 regions to 116 regions. However, there are no extreme weights. The minimum weight is 0.0746 , while the maximum weight is 3.0333. After weighting there is still a considerable range of regions with different values of ICT capital in the adjusted sample as is as can be seen from a the scatter

plot of weights and the ICT capital exposure in Figure 6.

Figure 6: Weight distribution for regional ICT capital



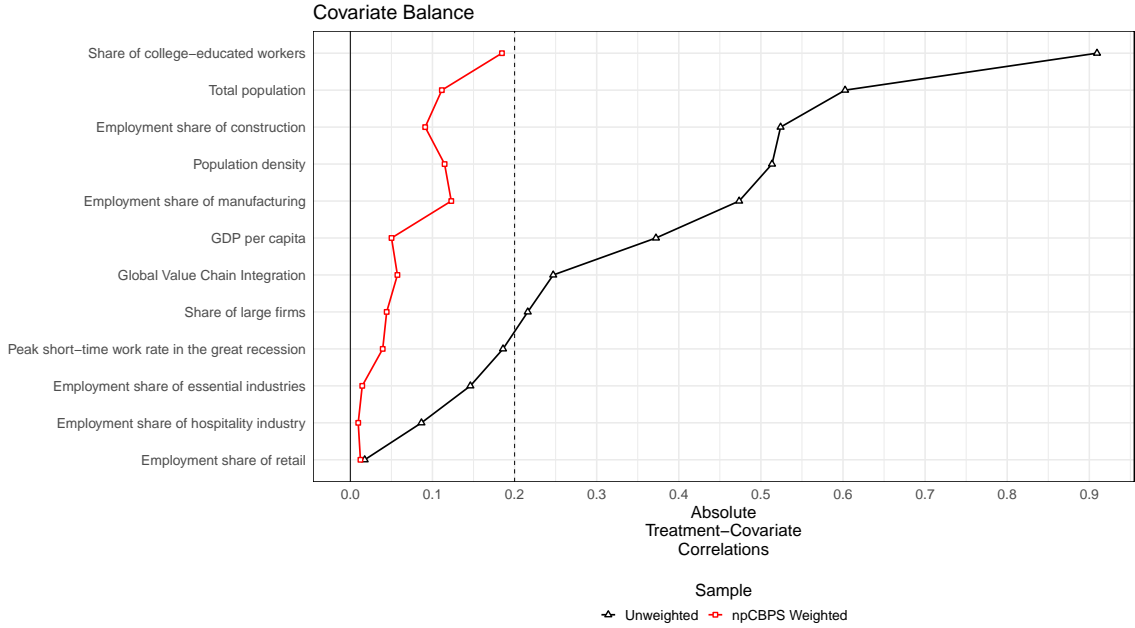
NOTE.- The figure presents the npCBPS weights of regions for the ICT capital measure against their ICT capital.

Note that the weights tend to be smaller for regions that have very high (e.g. Bonn) or very low ICT capital (e.g. Olpe) per worker compared to the average region. This illustrates that regions with exceptional amounts of ICT capital tend to be a worse comparison group than regions with average amounts of ICT capital, as they also differ more in the other variables that were included in the weighting procedure.

In particular, the large urban centres with very high ICT capital, exceeding €1500 per worker, receive very low weights. However, the distribution of the weights is left-skewed, with many low ICT capital regions having weights higher than 0.25, while large urban high ICT capital regions only have small weights.

Comparability across regions with different working-from-home potential Figure 7 shows that our weighting approach works well also in reducing the correlations between the working-from-home potential and key regional characteristics. The correlation of the education structure with working-from-home potential in the unweighted sample (0.909) is even higher than the one with ICT capital. However, it reduces to 0.185 in the weighted sample. Absolute Correlations with other variables such as total population or population density are also greatly reduced.

Figure 7: Covariate balance plot for working-from-home frequency



NOTE.- The figure shows the absolute correlations between key covariates and the regional working from home frequency both in the unweighted (black triangles) and the weighted sample (red squares).

To avoid using extreme weights, we trim 5% of regions with the highest and lowest weights. The weighting procedure for the working-from-home potential reduces the effective sample size to 125 regions. Similarly to the case for the ICT capital exposure, the distribution of weights along the working-from-home potential is left-skewed. Weights are very low only in urban regions with very high working-from-home frequency. These regions at top of the distribution, as shown in Figure C3 in the appendix, receive only very low weights.

Overall, the weighting procedure allows us to obtain a pseudo-sample of regions that are comparable in many dimensions potentially related to local labour market resilience during the pandemic. Using this weighting procedure, we examine in the next section the evolution of labour markets for regions with different levels of digitalisation.

5 Results

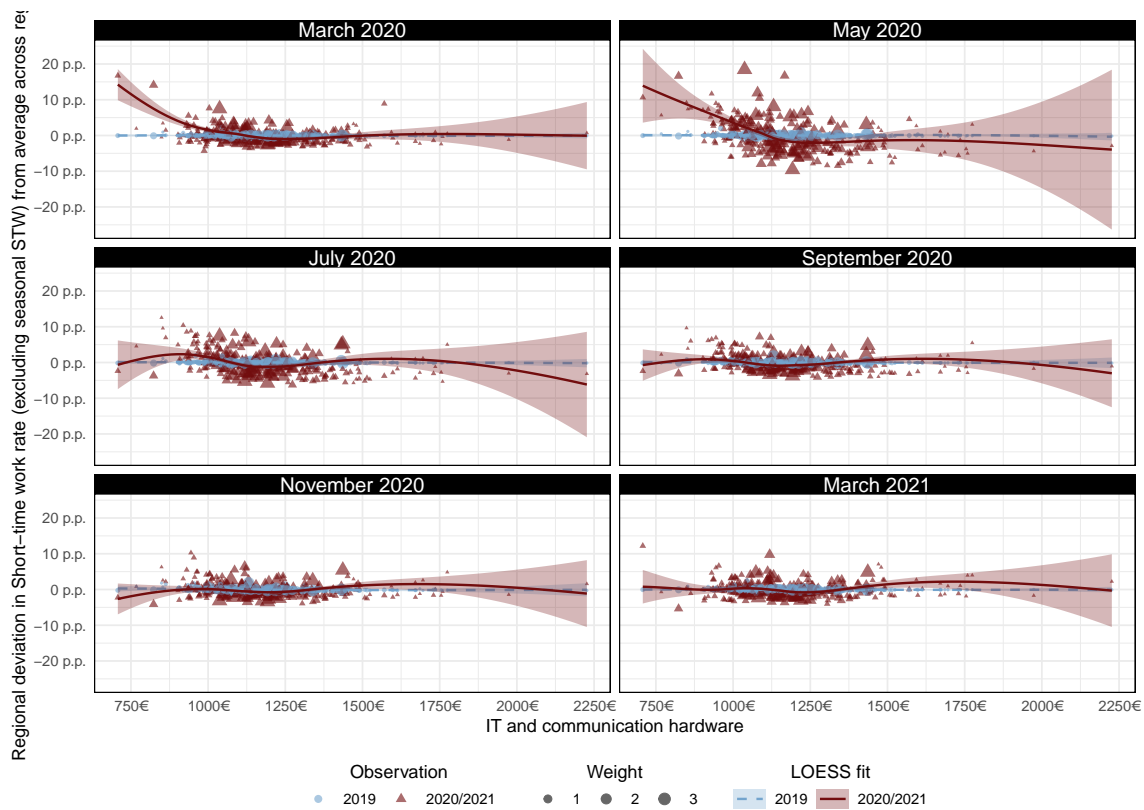
5.1 Digital capital

We start by analysing how the pre-crisis exposure to digital capital of regions have impacted their labour market performance during the COVID-19 crisis. The measure of the pre-crisis local exposure to ICT capital per worker is explained in section 4.1. 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, and then at the unemployment response.

Short-time work rate Figure 8 shows the deviation in short-time work rates from the regional average in March, May, July, September and November between 2019 and 2021. The 257 labour market regions are ordered by their level of exposure to ICT capital per worker. Blue dots represent regions in 2019, the reference year, while red triangles represent regions in a pandemic year, either 2020 or 2021. The size of the dots and triangles indicate the weight of a given observation. Additionally, weighted LOESS smoothing lines with 95% confidence intervals are displayed separately for the reference year (dashed blue line) and the pandemic year (thick red line).

Figure 8: Exposure-response-plots of ICT capital and short-time work rates



NOTE.- The figure reports deviation in short-time work rates for each 257 labour market regions with respect to the average over all regions. Short-time work rates are calculated as the number of workers using short-time work in a given month over the employment level in June 2019. Regions are ranked by their pre-crisis exposure to ICT capital. The npCBPS weight of observations is represented by the size of dots/triangles.

Figure 8 shows a sharp rise in short-time work rates at the start of the pandemic in regions with very low ICT capital. The effect of ICT capital on short-time work starts in March 2020 and remains significant until June 2020. The relative increase in short-time work for the low ICT regions becomes smaller and insignificant in July 2020 and has abated completely by September

2020. The negative effect of low ICT capital endowment on local employment decreases along the ICT capital distribution and remains significant until about the first quintile of the distribution of ICT capital (1010 € per worker).

To evaluate the strong pre-trends assumption, we show regions' deviations in short-time work rate from the regional average in 2019 in Figure D1 in the appendix. In contrast to the crisis months in 2020 there are no significant regional differences in short-time work along digital capital for the pre-crisis months.

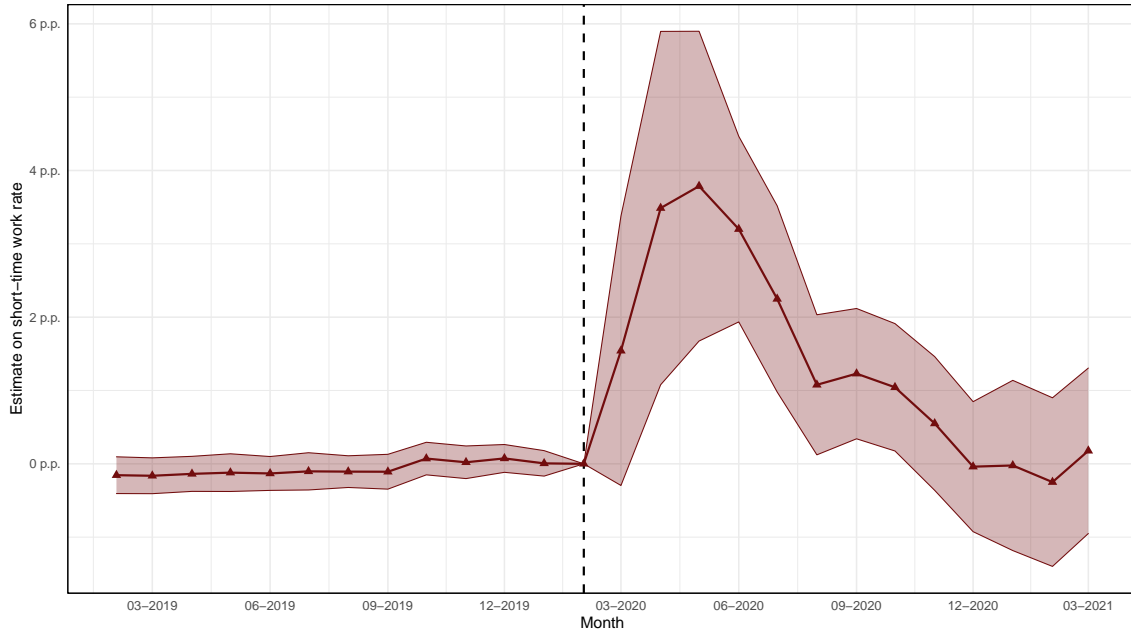
Short-time work rate in event-study plots To better follow the development of short-time work rates in regions at different points of the ICT capital distribution, we estimate event-study regressions. For this purpose, we collapse treatment exposure into a single dummy variable that has a value of one for regions with ICT capital per worker of less than 1010 € in 2019 (the first quintile of ICT capital per worker) and is zero otherwise. We then estimate a standard event-study specification that includes region- and time- fixed effects, as well as treatment-time interactions:

$$\text{STW-RATE}_{rt} = \sum_{t=-12, t \neq 0}^T \beta_t \text{LOW ICT CAPITAL}_r \times \text{TIME}_t + \sum_{t=-12, t \neq 0}^T \gamma_t \text{TIME}_t + \alpha_r + \varepsilon_{rt}. \quad (3)$$

We use February 2020 as the reference period because this coincides with the start of the first wave of a nationwide spread of the coronavirus, while the first lockdown was introduced by mid March 2020 in Germany. We estimate the effect of the treatment over 18 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.⁸

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

Figure 9: Event-study estimates of low ICT capital on short-time work rates



NOTE.- Short-time work rates are calculated as the number of workers using short-time work in a given month over the employment level in June 2019. The treatment corresponds to being in the first quintile of the regional ICT capital distribution. The figure displays both the 95% and 99% confidence intervals

The results of the event-study specification are shown in Figure 9 where we present the coefficients of the interactions between the time indicators and the dummy variable for a low level of ICT capital. For the months before February 2020, the estimated coefficients are very close to zero, indicating that regions with low and high ICT capital experienced parallel trends in short-time work rates prior to the COVID-19 pandemic. In April 2020, the average difference between regions with low ICT capital and the rest rises to 4 percentage points. This amounts to a ca. 20% higher short-term work rate in regions in the bottom quintile of ICT capital, given that the short-term work rate raised on average by 20 percentage points in Spring 2020. Thereafter, the difference between low and high ICT capital regions gradually diminishes and it returns to its close to zero pre-crisis level by November 2020.

The event-study analysis confirms the exposure response analysis: regions with a low level of ICT capital endowment experienced stronger increases in short-time work that lasted throughout 2020. In other words, local labour markets less exposed to digital capital were less able to adapt to the crisis and needed to use short-time work schemes to a larger extent. However, the event analysis suggests that the impact of ICT capital on local labour markets lasted until Autumn 2020.

Unemployment rate One question that immediately arises from this first result is whether regions with low ICT capital endowments also experienced higher unemployment increases or whether short-time work schemes prevented unemployment increases in low ICT regions. To answer this question, we compare unemployment rates in 2019 and 2020 along the regional distribution of pre-crisis endowments in ICT capita.

Figure D2 shows that the response profile of unemployment rates is the same in 2020 compared to 2019 for all levels of ICT capital per worker. Moreover, the pattern stays almost unchanged throughout the crisis. Most interestingly, the regions with low ICT capital endowments per worker did not experience stronger increases in unemployment than other regions.⁹ Thus, the higher take-up of short-time work in low ICT regions likely prevented a sharper rise in unemployment during the crisis.

5.2 Working-from-home potential

One channel through which digital capital influenced labour markets during the pandemic is through the ability to work remotely. While remote work depends on the nature of tasks on the job, it also depends on digital capital of firms, such as the provision of laptops, adequate software and VPN connections. The speed at which firms and their employees could use remote work efficiently also depends on their pre-crisis experience in using remote work arrangements. To analyse the effect of working-from-home on employment responses, we use the pre-crisis frequency of remote work at the occupation level. A region’s working-from-home potential is the sum of occupations working-from-home frequency weighted by the region’s occupation employment share, as explained in section 4.1.

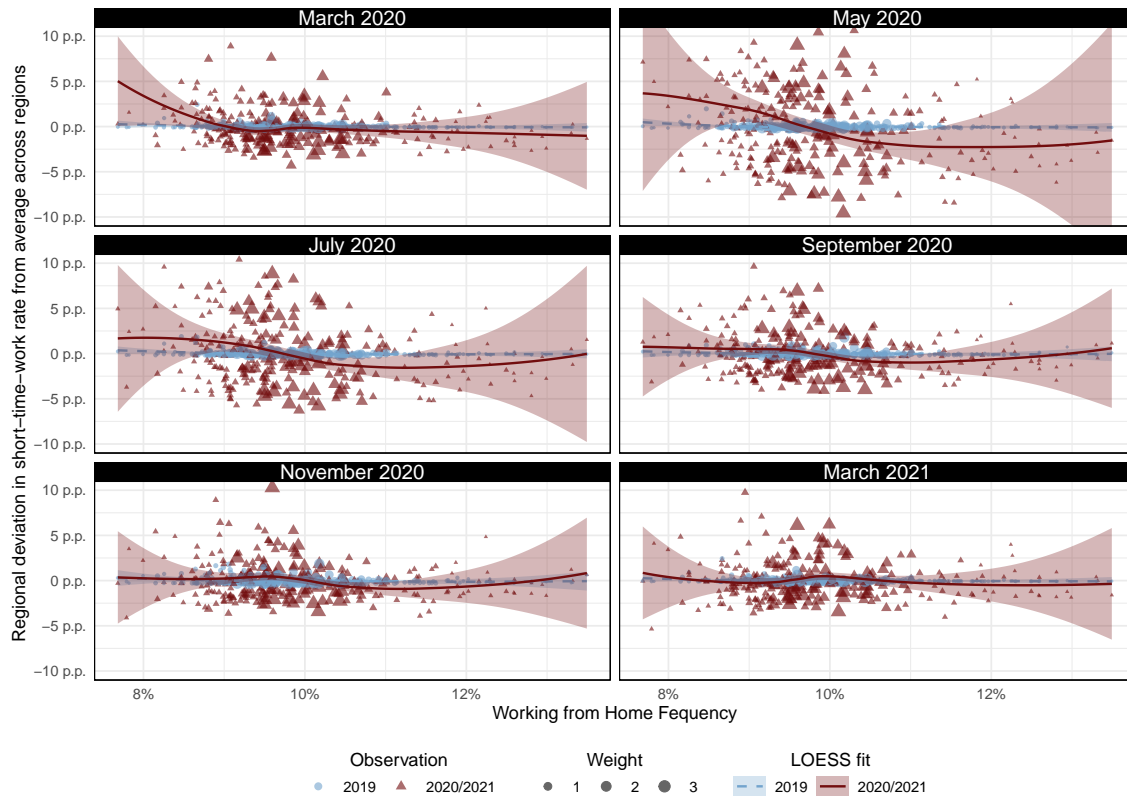
This step complements the ICT capital analysis presented above. It also complements previous work on the role of working-from-home during the crisis by Alipour et al. (2020). First, using a similar measure for working-from-home possibilities (i.e. the working-from-home frequency in 2018), we can replicate and compare results from Alipour et al. (2020) with different methods and newer data. Second, we analyse whether the effects of working-from-home on local short-time work rates found in the first two months of the pandemic persisted over time. Lastly, we explore whether there are heterogeneous effects across regions with different ICT capital.

Short-time work rate Figure 10 presents exposure-response plots for the working-from-home frequency on short-time work rates, following the same procedure as with ICT capital. The relation to short-time work is less clear than for ICT capital. Still, short-time work rates are initially higher in regions in the lower part of the working-from-home frequency distribution.

⁹Figure D3 in the appendix shows that evolution of unemployment in 2019 and 2018 to address the strong pre-trend assumption.

The deviation is statistically insignificant for regions with very low working-from-home potential. However, regions in the first quintile of the distribution have significantly higher short-time work rates than the average from April to June 2020 compared to the same months in 2019. Conversely, short-time work rates are lower in regions above the median, and the negative deviation is statistically significant for regions close to the median from April until July 2020. After July 2020, the regional deviations in short-time work rates become smaller and statistically insignificant for all levels of the working-from-home frequency.

Figure 10: Exposure-response-plots of working-from-home frequency and short-time work rates



NOTE.- The figure reports deviations in short-time work rates for each 257 labour market regions with respect to the average over all regions. short-time work rates are calculated as the number of workers using short-time work in a given month over the employment level in June 2019. Regions are ranked by their pre-crisis working-from-home frequency. The npCBPS weight of observations is represented by the size of dots/triangles.

The pre-crisis evolution of short-time work rates along the working-from-home frequency distribution is presented in Figure D6 in the appendix. Apart from a small deviation in May 2019, there is no significant pre-trend all along the working-from-home frequency distribution.

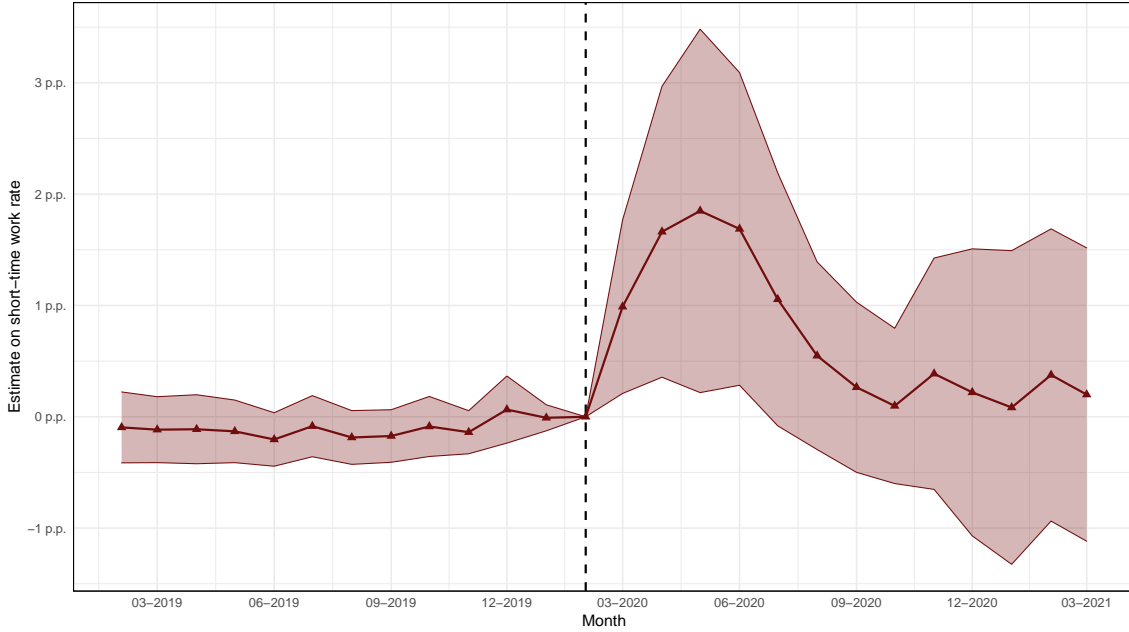
Short-time work rate in event-study plots We again use event-study regressions to visualise the dynamics of the effect of a region's working-from-home potential during the crisis. To

this end, we estimate the following specification, where $\text{LOW_WFH_FREQUENCY}_r$ is an indicator for regions where the pre-crisis working-from-home frequency is in its first two quintiles:¹⁰

$$\text{STW-RATE}_{rt} = \sum_{t=-12, t \neq 0}^T \beta_t \text{LOW_WFH_FREQUENCY}_r \times \text{TIME}_t + \sum_{t=-12, t \neq 0}^T \gamma_t \text{TIME}_t + \alpha_r + \varepsilon_{rt}. \quad (4)$$

We plot the estimates of this specification in Figure 11. The event-study coefficients are positive and significant for the time between March and July 2020, with the maximum being a 2 p.p. higher short-time work rate for regions with a low working-from-home potential. This hints at a small and temporary effect of working-from-home potential on short-time work usage.

Figure 11: Event-study estimates for low working-from-home potential on short-time work rates



NOTE.- Short-time work rates are calculated as the number of workers using short-time work in a given month over the employment level in June 2019. The treatment corresponds to being in the first quintile of the working-from-home frequency distribution (a working-from-home frequency below 9% in 2018) .

Unemployment rate Lastly the question arises, whether there were different unemployment responses depending on the working-from-home potential of a region. Figure D5 in the appendix shows the unemployment responses throughout the pandemic along the working-from-home frequency distribution. Similarly to what we find for digital capital, there are no differences in unemployment rates between 2019 and 2020 at different points of the working-from-home frequency distribution.

¹⁰Regions below the first quintile of the working-from-home frequency distribution had at most 9% of employees frequently working-from-home in 2018.

5.3 Digital capital and working-from-home

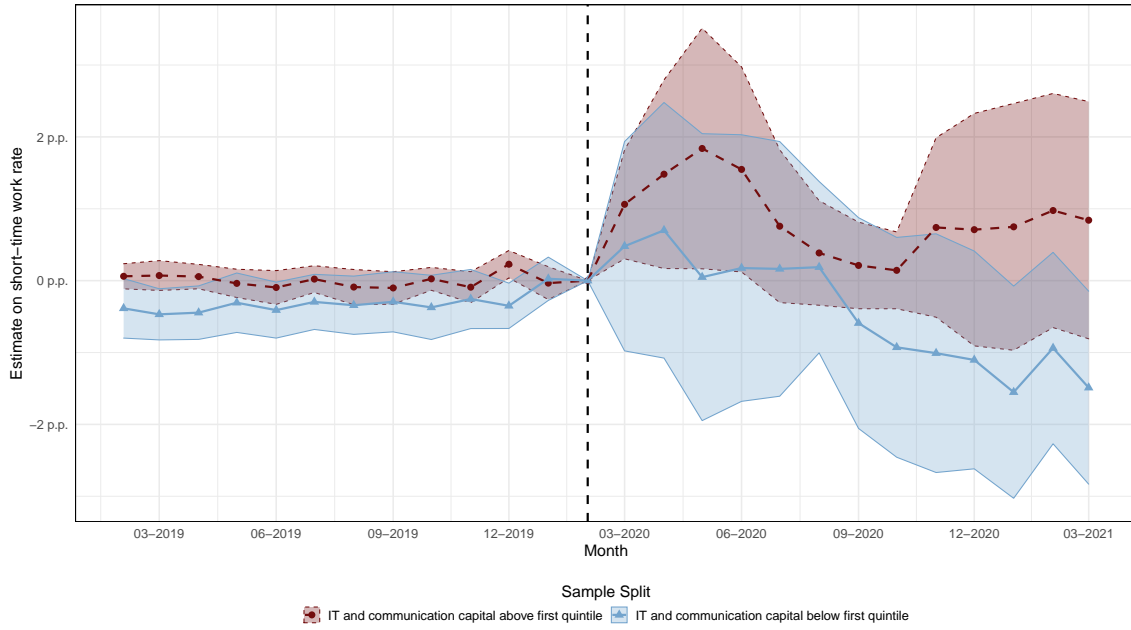
We have shown that both digital capital and working-from-home reduced the take-up of short-time work during the pandemic. In fact, digital capital and working-from-home are likely complementary as efficient remote work requires good digital equipment, and the necessity to work remotely made digital capital even more valuable during the first months of the crisis. To substantiate this hypothesis, we investigate how the role of working-from-home depends on a region's pre-crisis exposure to digital capital.

To this end we split the sample between local labour market with high vs. low exposure to digital capital. We then estimate the effect of working-from-home for these two sub-samples separately. Figure 12 presents the estimates of equation 4, where the treatment is having a low WfH potential, for two sub-samples. In red we show regions where the exposure to ICT capital is above the first quintile, while blue indicates lower ICT capital exposures. For regions with higher digital capital, a low WfH potential increases the usage of STW. Local labour markets with a low share of jobs that can be performed remotely had short-time work rates that were 2 percentage points higher than other regions during the first lockdown. While the difference fades out during the summer, local labour markets with a low WfH potential have again higher short-time work rates in autumn 2020 when a second lockdown was in place, however the difference is not significant anymore.

In contrast, we do not observe any significant relationship between STW and the WfH potential for regions at the bottom of the ICT distribution, as shown by the almost flat blue line. In other words, regions with an employment structure that allowed remote work experienced a lower incidence of short time work only if they had enough ICT capital.

This suggests that the possibility to work from home shielded workers and firms from the economic consequences of the pandemic in spring 2020 but only if a minimum endowment in digital capital could be used right away. In regions with very low digital capacities, remote work was unlikely to be a fast replacement of on-site work as the equipment and know-how was not readily available. These findings suggest that ICT capital and WfH potential of jobs are complementary.

Figure 12: Exposure-response-plot of low working-from-home potential and short-time work by low and high digital capital



NOTE.- Short-time work rates are calculated as the number of workers using short-time work in a given month over the employment level in June 2019. The treatment corresponds to being below the first quintile of the working-from-home frequency distribution (a working-from-home frequency below 9% in 2018). The estimates for low and high IT capital sub-samples are in different colours. Blue indicates high IT capital regions while red indicates low IT capital regions.

6 Discussion

We now discuss the implications and limitations of the results, as well as avenues for further research.

We find that digital capital, as measured by exposure to ICT capital, reduced the negative impact of the pandemic on local labour markets. Some channels through which ICT capital played a role were specific to the COVID-19 pandemic, such as the need to work from home at the onset of the pandemic, and the reduced likelihood of spreading the virus within firms that were able to effectively reduce contacts. We do find that working-from-home led to lower short-time work take-up only in local labour markets with a high exposure to digital capital. But Working-from-home shielded workers from short-term work only in the first months of the pandemic when strong contact restrictions were in place. However, the effect of digital capital on short-time work is stronger and longer lasting than the effect of working-from-home as we can see by comparing Figure 9 and Figure 11. The effect of digital capital on STW diminished only when labour markets started to recover. This suggests that digital capital influenced labour

market resilience during the crisis through other channels than working-from-home.

Other channels are likely to be similar to those linking ICT to productivity, particularly to enable faster sharing information and improve decision-making within organisations.¹¹ Indeed, the pandemic made ICT even more important for firm organisation and decision making, for example, to swiftly deal with the disruption of supply chains. The recognition of the wide benefits of ICT during the pandemic is likely to have long-term effects on firms and the labour market.

It is difficult to identify the causal effect of digital capital on short-time work in our setting. The approach we use hinges on two main assumptions that we discuss further here. The local exposure to digital capital depends on a region’s industry mix and the industries’ endowment in digital capital. One assumption requires that this measure reflects exposure to digital capital and not other factors related to the local industry mix. For this purpose, we control for a wide range of controls including the regions’ income per capita, demographic structure, and 1-digit industry employment shares. In particular, we control for the local employment share of the hospitality sector, which suffered the most during the Covid-19 pandemic. To further address the particularities of the Covid-19 pandemic, we control for the local integration into global value chains, which were heavily disrupted by the pandemic. We also control for local short-time work rates during the Great Recession to capture past regional experience during a crisis that might also be related to its industry structure. Moreover, we show that after the weighting procedure, regions are comparable in a wide range of characteristics such as various labour market outcomes, firm size distribution, age structure and internet access distribution. Even though we control for many potential confounders, we cannot completely rule out that the local 2-digit industry structure before the pandemic is correlated with some unobservable characteristics that might influence employment outcomes during the crisis.

The second assumption of our approach implies that a given industry contributes equally to the digital capital *exposure* in all regions. In other words, the measure does not capture the fact that the same industry may have different levels of digital capital in two different regions. Our local exposure to digital capital can be interpreted as the *potential* digital capital endowment of a region given the industry structure of that region. Regional differences in digital capital within detailed industries are likely endogenous to a local labour market as it depends on local firms’ abilities and willingness to invest in new technologies which is related to managerial skills and productivity. Instead, we use a more exogenous measure that captures how feasible it is to use digital capital given the production processes of the industries located in a region. Exposure measures based on a region’s employment shares across industries or occupations have been

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

widely used in the local labour market literature.

Next, we identify several challenges for future research. First, analysing the implications for regional inequalities in more details and with a longer time horizon is a policy-relevant task for future research. The results suggest that the spatial digital divide brought further employment inequalities with the pandemic but only in the short to medium run. The higher use of short-time work in local labour markets with low digital capital has likely prevented longer term effects due to unemployment and firm closures. However, further research and other data is required to fully address this question.

Data on digital capital at the regional level, or both the industry and regional levels, would be useful to provide a picture of actual digital capital differences across regions and explore further questions related to the implications of the spatial digital divide. Regional data on digital capital would be particularly interesting 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) but the effects on the regional digital divide and its implications have not been explored yet.

Second, the dynamic of digital capital adoption during the pandemic is an important aspect that we cannot study with current data at hand. While pre-crisis digital capital is an important determinant of the evolution of short-time work in the first phase of the pandemic, it loses its predictive power over time. This might be explained by the fact that the pandemic shock to labour markets was largest in 2020 and abated quickly due to the relaxation of rules for firms after the first COVID wave. Still, the lack of persistence in the effect of pre-crisis digital capital might also be due to the widespread adoption of digital capital during the pandemic and the potential catching up of regions lagging behind by the end of 2020.

Finally, further research could explore how other dimensions of digitalisation shape labour market resilience. We focus here on digital capital endowments and working-from-home feasibility from the job perspective. However, digital skills of the labour force, for example, could also matter. Regions where the workforce already possesses a high level of digital competency could adopt digital capital more quickly and use it to its fullest potential to overcome the problems created by the pandemic.

7 Conclusion

This article documents how German local labour markets responded to the COVID-19 shock in the short and medium run, and how digitalisation affected their employment responses. Local labour markets experienced vastly different changes in short-time work rates in the short run

(first 4 months) of the pandemic. However, regions quickly converged to lower and similar short-time work rates that have since persisted.

Accounting for regional characteristics, we show that a low digital capital endowment before the pandemic contributed to higher short-time work rates during the pandemic in the short to medium run (up to 8 months). A lack of remote work capacity also led to higher short-time work rates in the short run, a finding that is consistent with early work on the COVID-19 pandemic. However, as soon as restrictions on on-site work were lifted, the effect of working-from-home potential on local employment disappears. The short-run effect of working-from-home potential is especially striking in regions with high digital capital, while regions with low digital capital have had consistently higher short-time work usage irrespective of their working-from-home potential. Indeed, both the possibility to bring tasks home and adequate equipment and software are needed for remote work. As a result, the share of teleworkable jobs does not make a difference for short-time work take-up in regions that were not endowed with enough digital capital before the pandemic outbreak. While a region's exposure to digital capital and working-from-home potential affected its short-time work usage, it had however no impact on its unemployment rate.

Overall, our findings suggest that digitalisation has improved the resilience of regions to the shock of the pandemic. Moreover, it seems that short-time work schemes have been successful in cushioning the potential negative employment effects of the crisis that were larger in regions with low digital capital endowments. Indeed, by summer 2020, regions at the bottom of the digital capital distribution had converged to similar short-time work rates than other regions and the unemployment rate had reached its pre-crisis level by the end of 2021 in all regions.

While digital capital was essential at the beginning of the pandemic, regional differences in digitalisation have not led to persistent regional inequalities in employment. The likely positive effect of short-time work schemes during the early phase of the COVID-19 pandemic is consistent with the literature on short-time work as an effective tool to reduce layoffs against large temporary shocks (Giupponi et al., 2022; Giupponi and Landais, 2018).

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A Data

Table A1: List of industries with information on ICT capital from EU Klems database

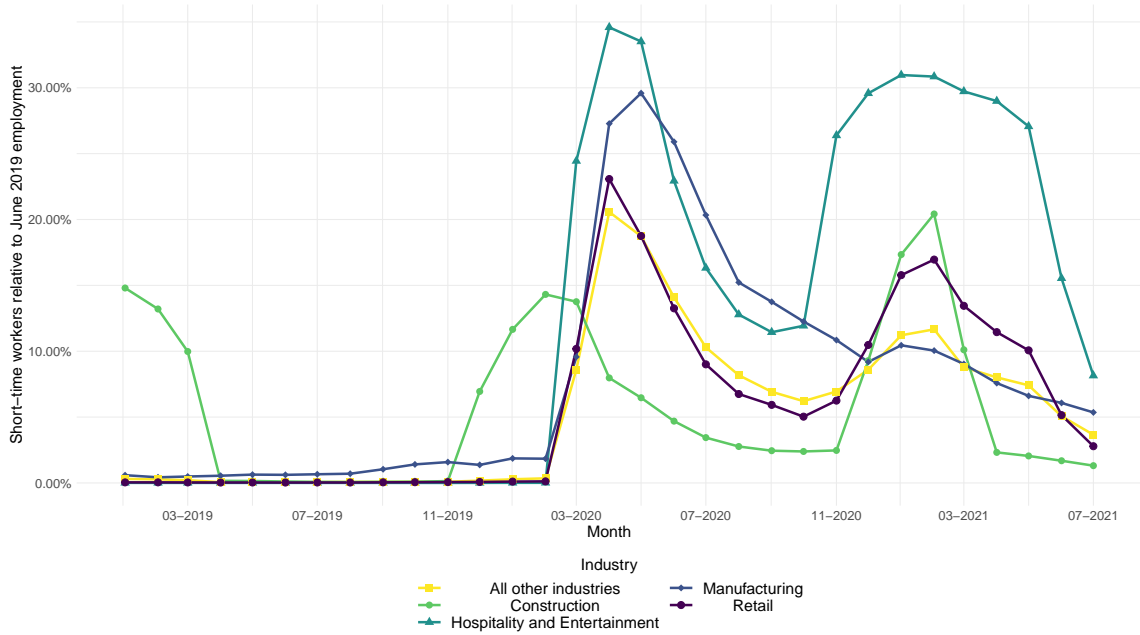
1	Agriculture, forestry and fishing
2	Mining and quarrying
3	Food products, beverages and tobacco
4	Textiles, wearing apparel, leather and related products
5	Wood and paper products
6	Coke and refined petroleum products
7	Chemicals and chemical products
8	Basic pharmaceutical products and pharmaceutical 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.

B Broad industry-composition and short-time work across local labour markets

The short-time work rate varied greatly across different sectors of the economy. Figure B.1 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.1: 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 within-sector differences in finer grained industry employment shares (i.e. short-time work rate differences 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:

$$\text{DEVIATION}_r = \sum_r E_{ir} \times STW_{ir} - \sum_i E_i \times STW_i$$

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:

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

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

$$\text{COMPOSITION}_r = \sum_i (E_{ir} - E_i) \times STW_i$$

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:

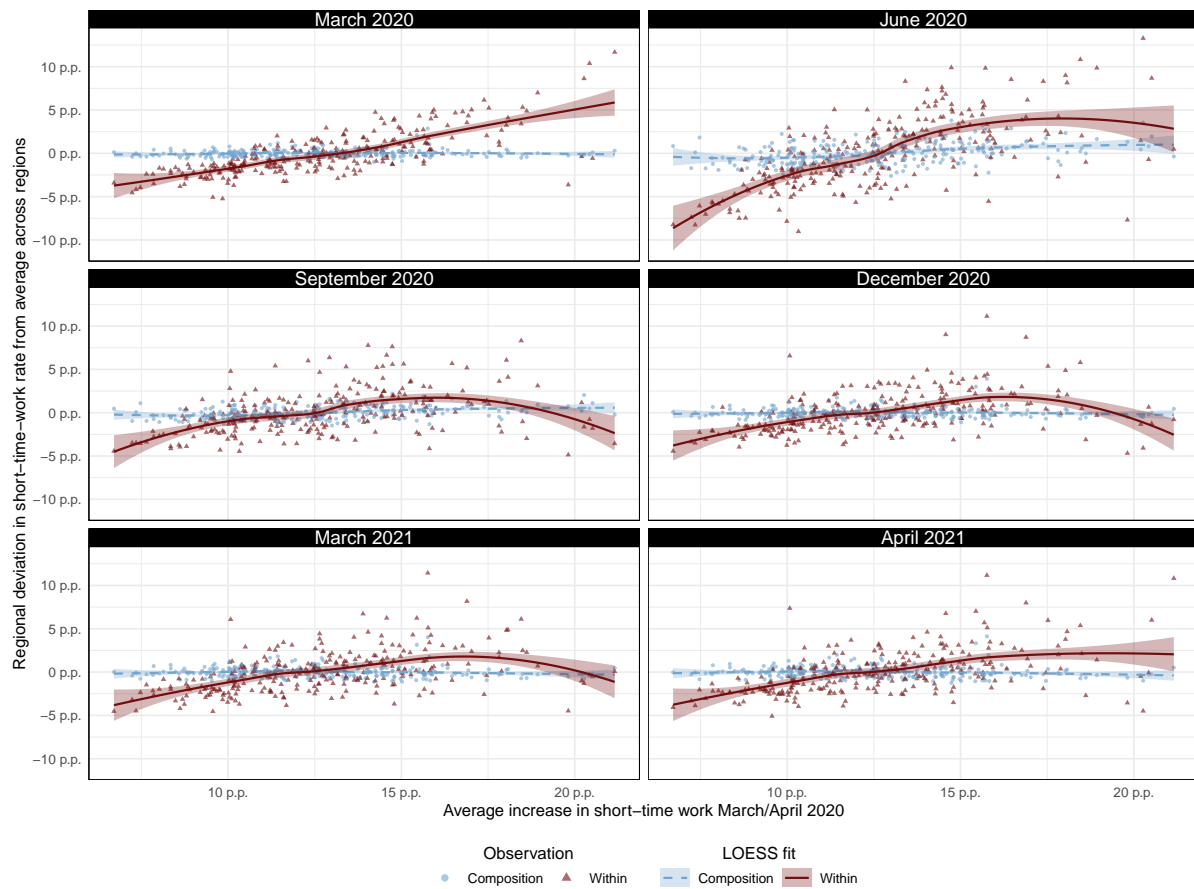
$$\text{WITHIN}_r = \sum_i (STW_{ir} - STW_i) \times E_{ir}$$

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.2 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.

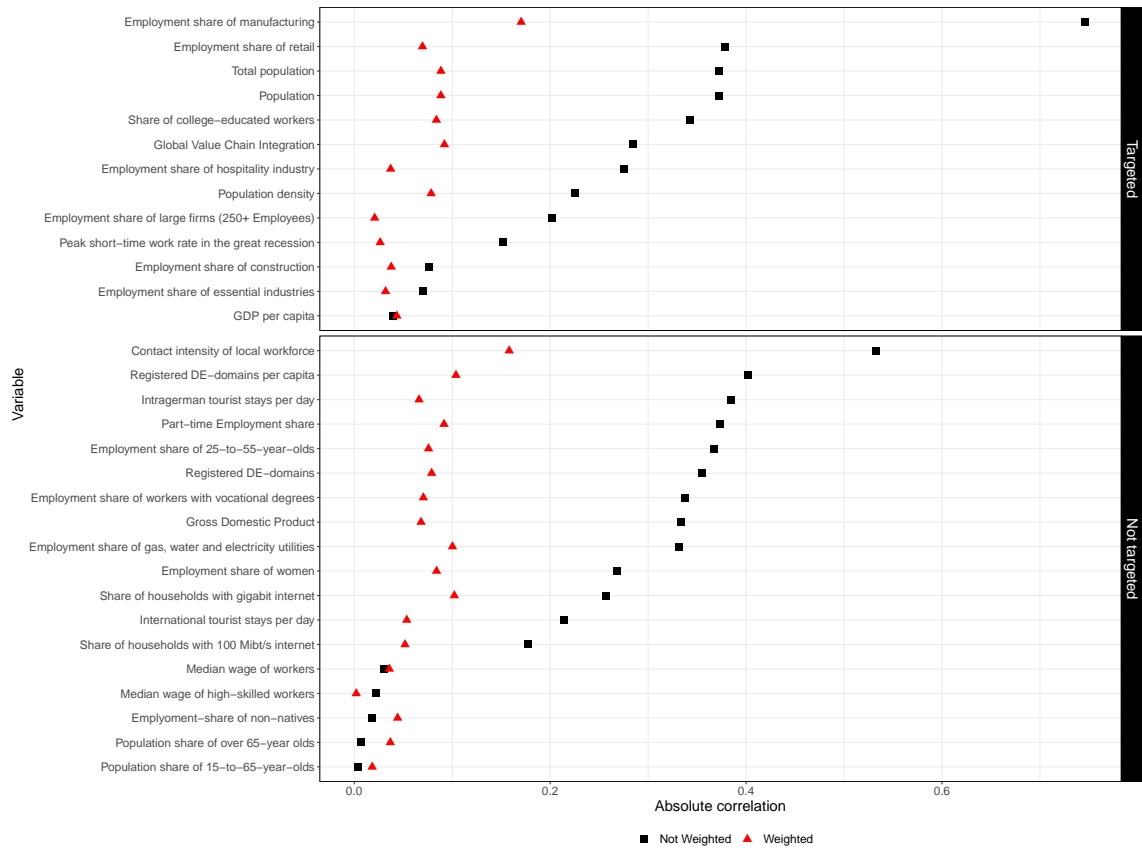
Figure B.2: Decomposition of regional short-time work rates into industry-composition and within-industry components



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.

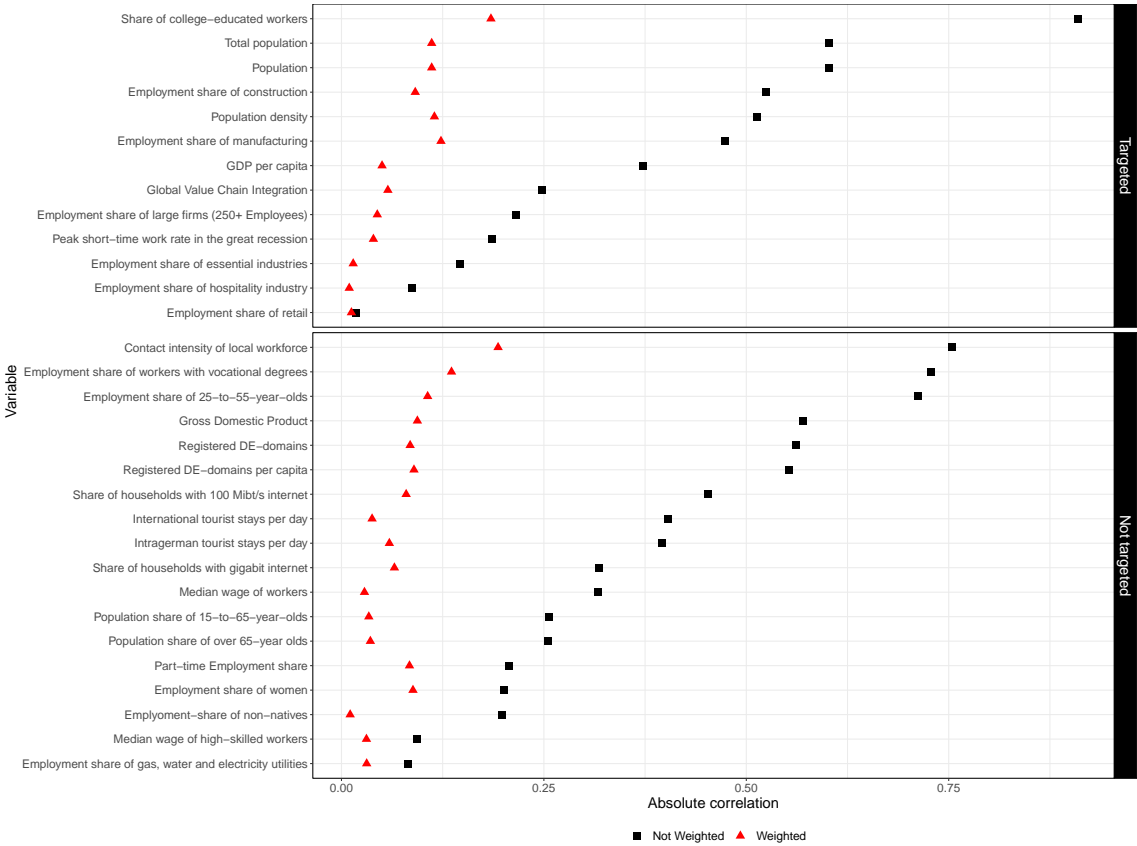
C Empirical strategy

Figure C1: Balance for non-targeted covariates for digital capital



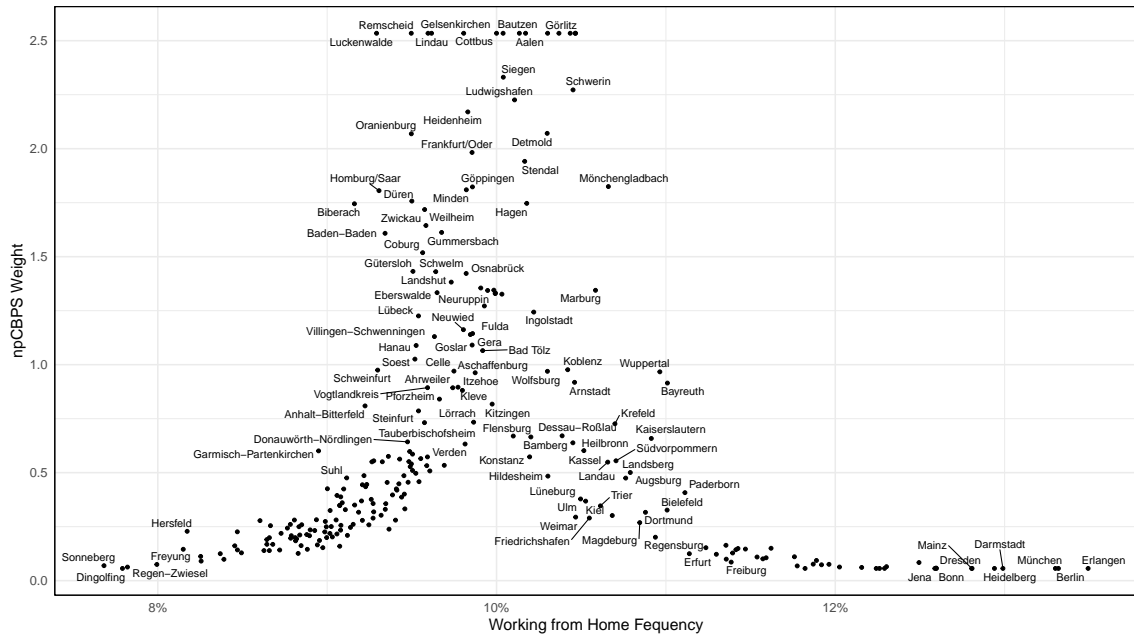
NOTE.- The figure shows the absolute correlations between both targeted and non-targeted covariates in our npCBPS weighting procedure and the measure for exposure to digital capital both in the unweighted (black squares) and the weighted sample (red triangles).

Figure C2: Balance for non-targeted covariates for the Working from Home frequency



NOTE.- The figure shows the absolute correlations between both targeted and non-targeted covariates in our npCBPS weighting procedure and the measure for the Working from Home frequency both in the unweighted (black squares) and the weighted sample (red triangles).

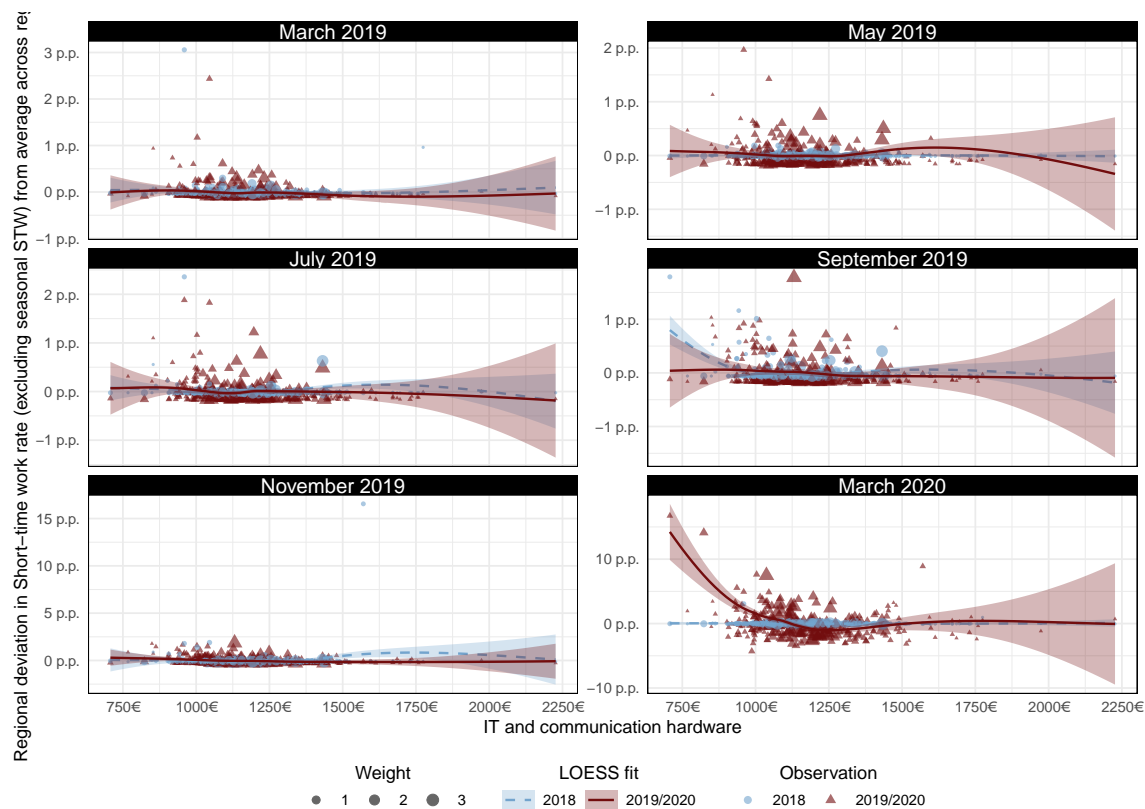
Figure C3: Weight distribution for the Working from Home frequency



NOTE.- The figure presents the npCBPS weights of regions for the Working from Home frequency plotted against the measure itself.

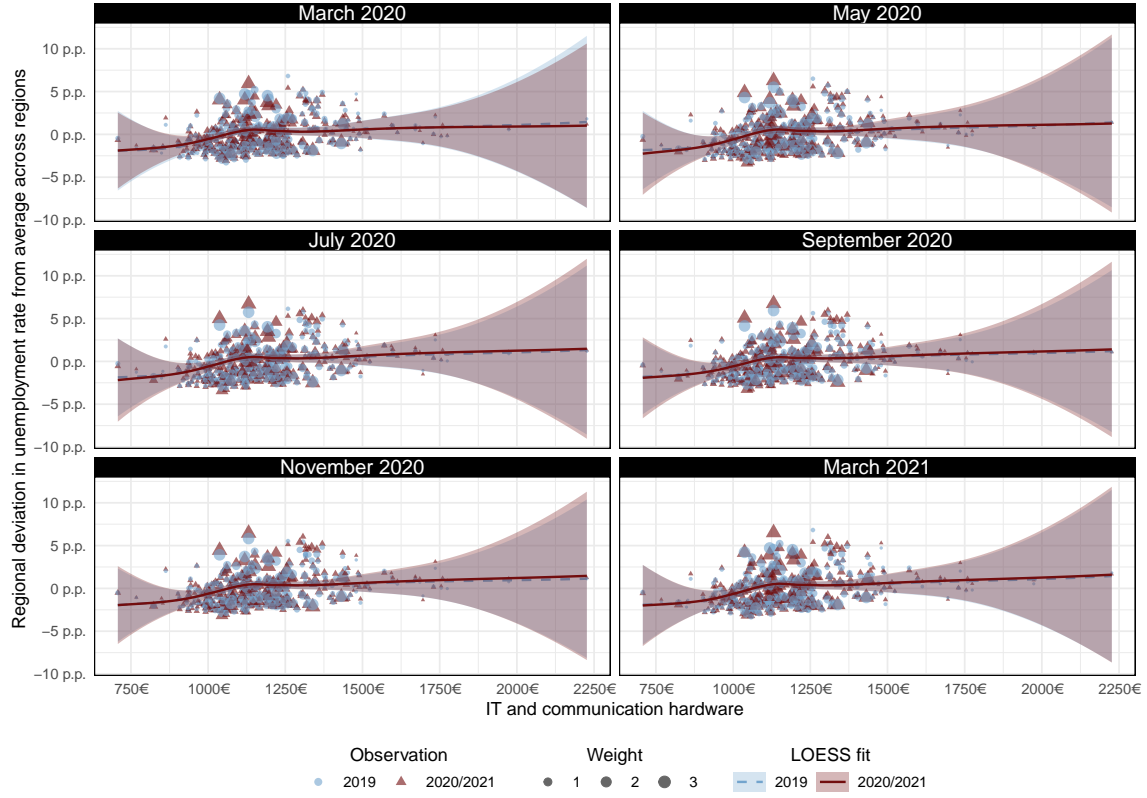
D Additional exposure-response plots

Figure D1: Pre-trend digital capital and short-time work rates



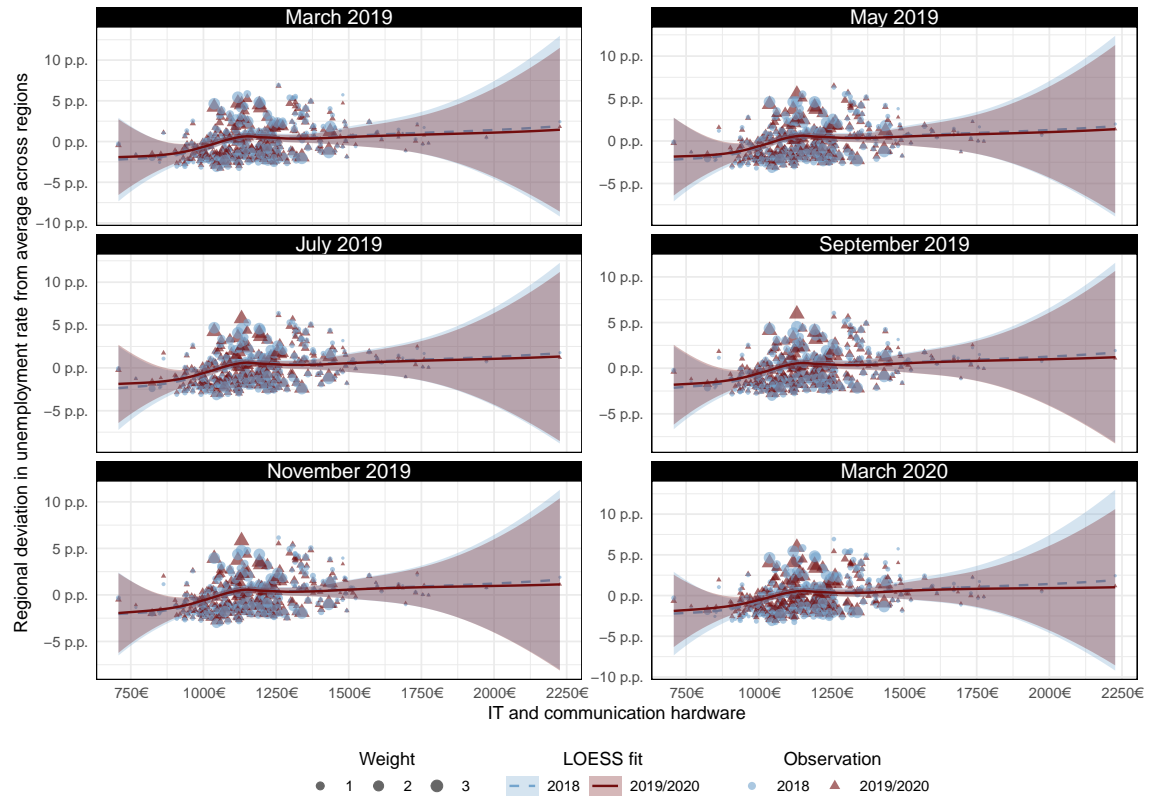
NOTE.- The figure reports deviation in short-time work rates for each 257 labour market regions with respect to the average over all regions for pre-crisis months. Short-time work rates are calculated as the number of workers using short-time work in a given month over the employment level in June 2019. Regions are ranked by their pre-crisis exposure to digital capital.

Figure D2: Exposure-response-plots of digital capital and unemployment rates



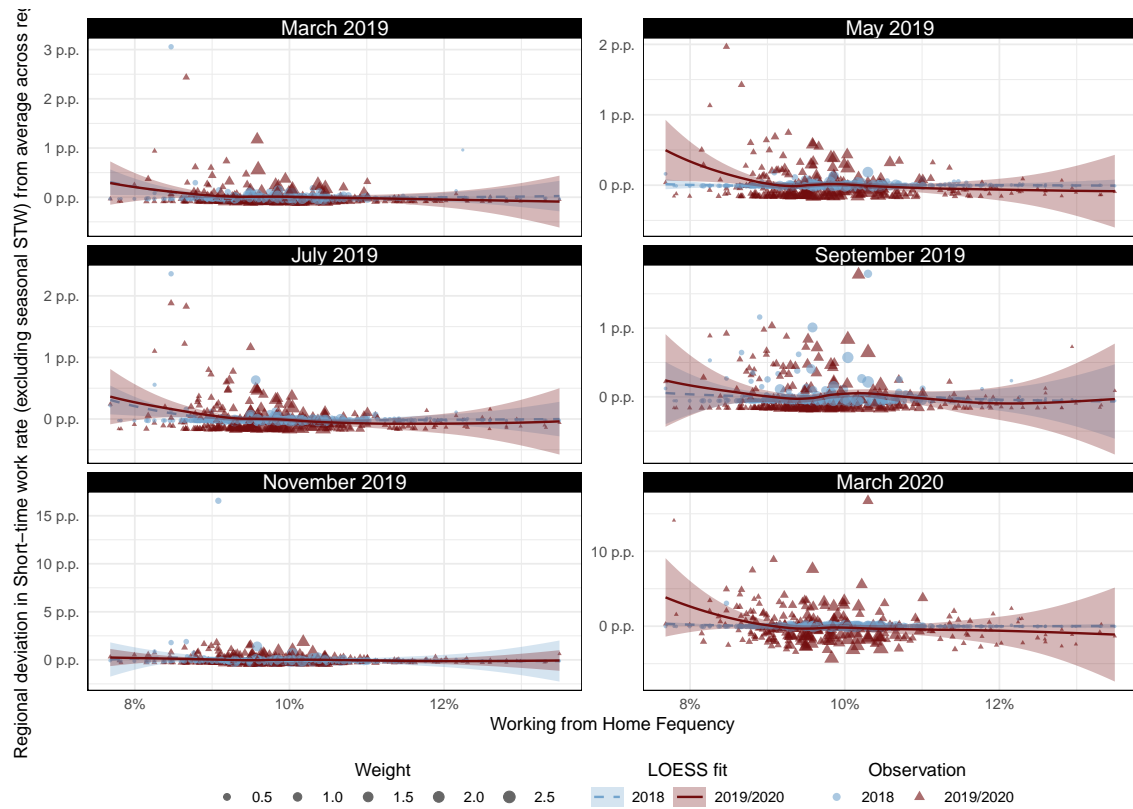
NOTE.- The figure reports deviation in unemployment rates for each 257 labour market regions with respect to the average over all regions. Unemployment rates are calculated as the number of unemployed individuals in a given month over the employment level in June 2019. Regions are ranked by their pre-crisis exposure to digital capital. The npCBPS weight of observations is represented by the size of dots/triangles.

Figure D3: Pre-trend digital capital and unemployment rates



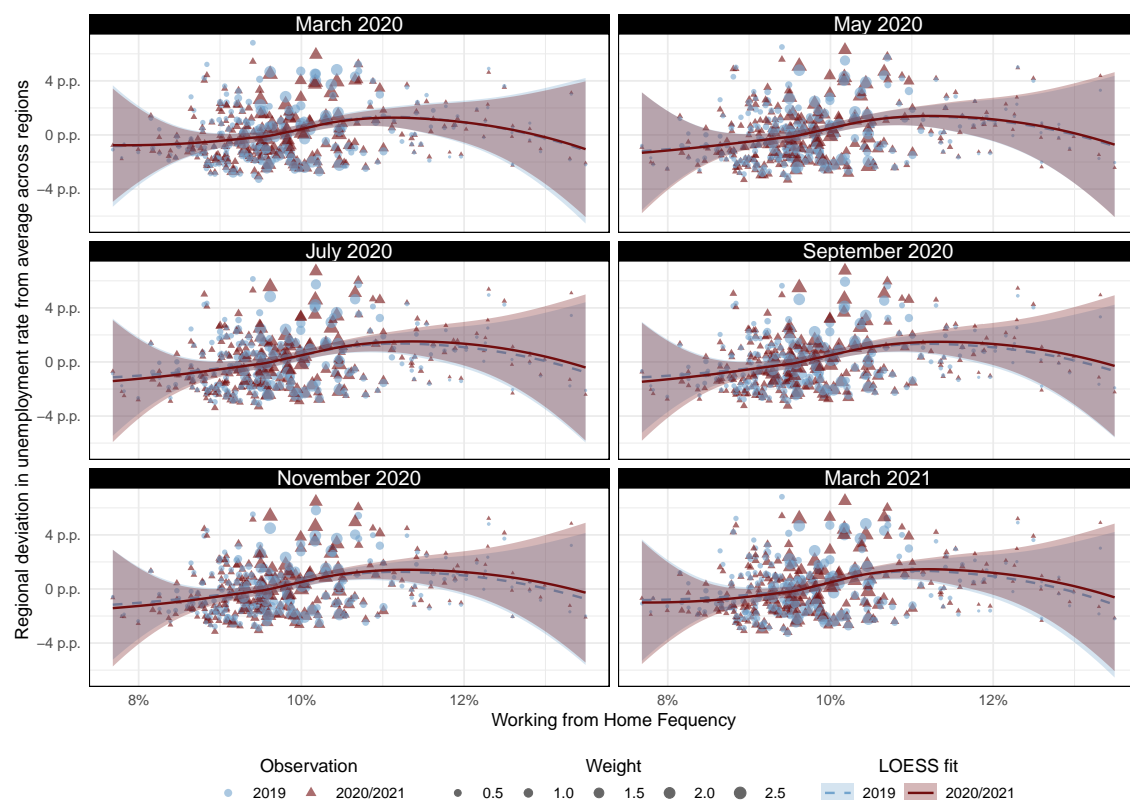
NOTE.- The figure reports deviation in unemployment rates for each 257 labour market regions with respect to the average over all regions for pre-crisis months. Regions are ranked by their pre-crisis exposure to digital capital.

Figure D4: Pre-trend Working-from-home frequency and short-time work rates



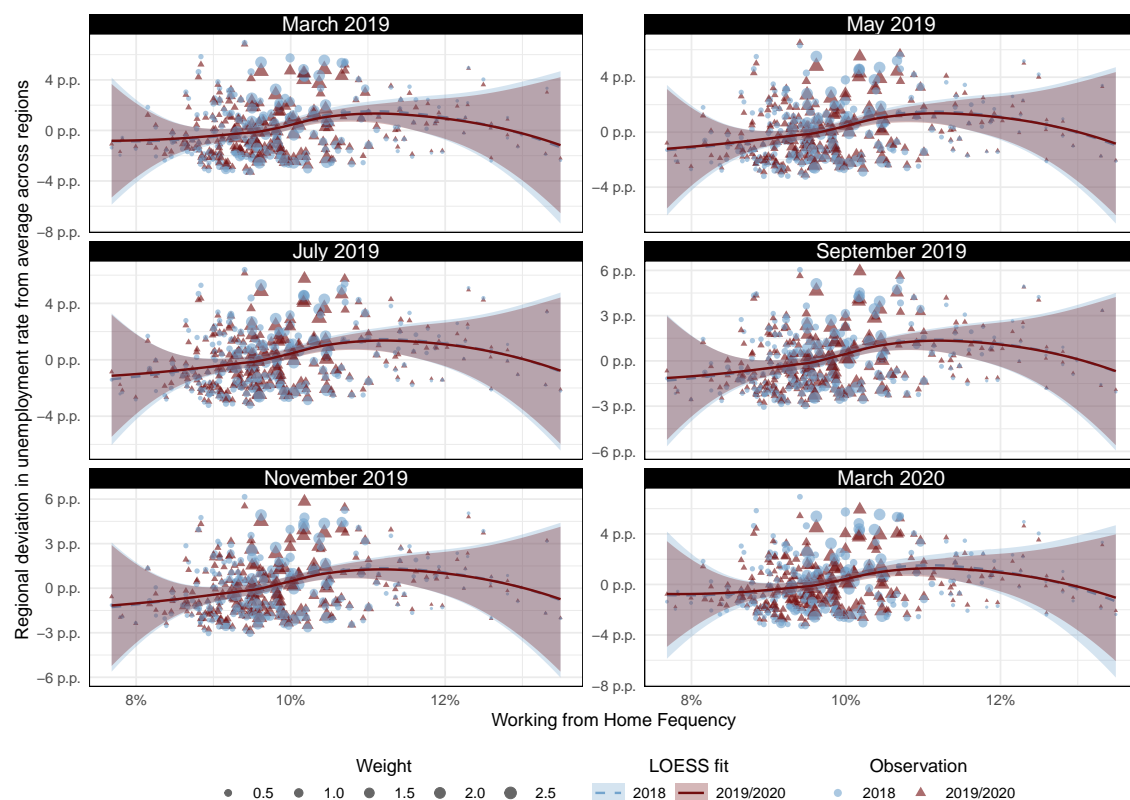
NOTE.- The figure reports deviation in short-time work rates for each 257 labour market regions with respect to the average over all regions for pre-crisis months. Short-time work rates are calculated as the number of workers using short-time work in a given month over the employment level in June 2019. Regions are ranked by their pre-crisis Working from Home frequency.

Figure D5: Exposure-response-plots of working-from-home frequency and unemployment rates



NOTE.- The figure reports deviations in unemployment rates for each 257 labour market regions with respect to the average over all regions. Regions are ranked by their pre-crisis working-from-home frequency. The npCBPS weight of observations is represented by the size of dots/triangles.

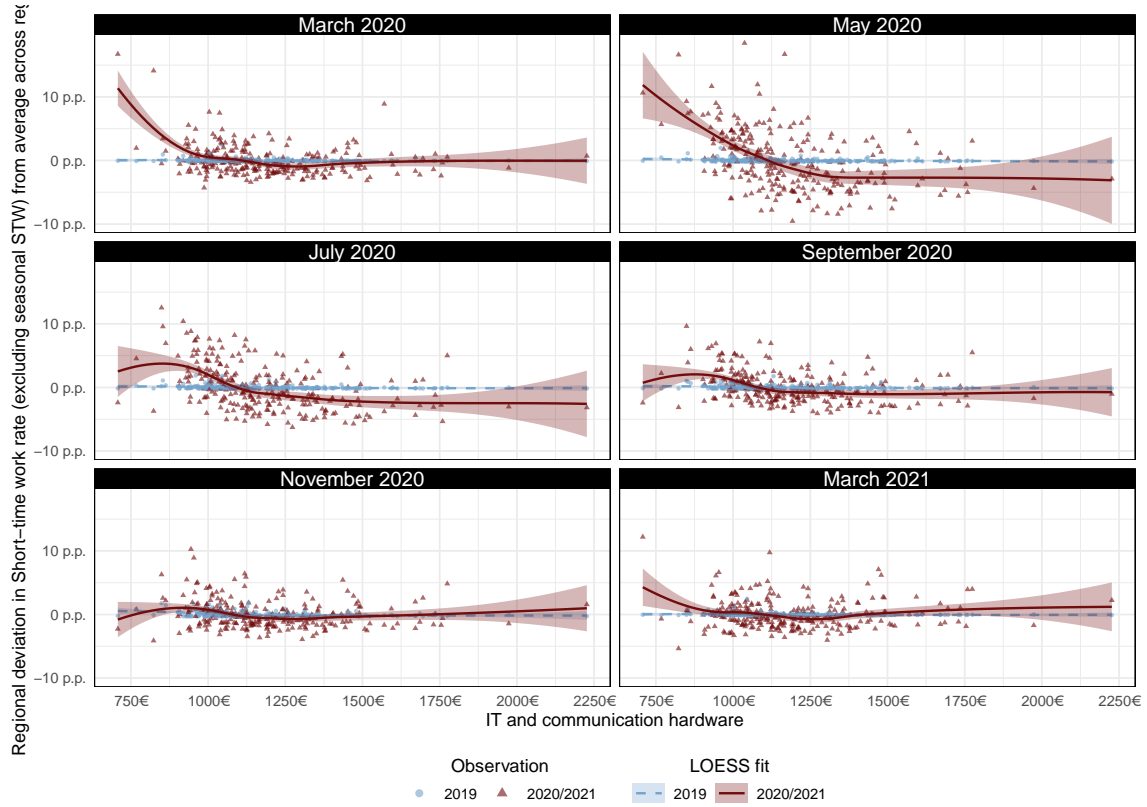
Figure D6: Pre-trend Working from Home frequency and unemployment rates



NOTE.- The figure reports deviation in unemployment rates for each 257 labour market regions with respect to the average over all regions for pre-crisis months. Regions are ranked by their pre-crisis Working from Home frequency.

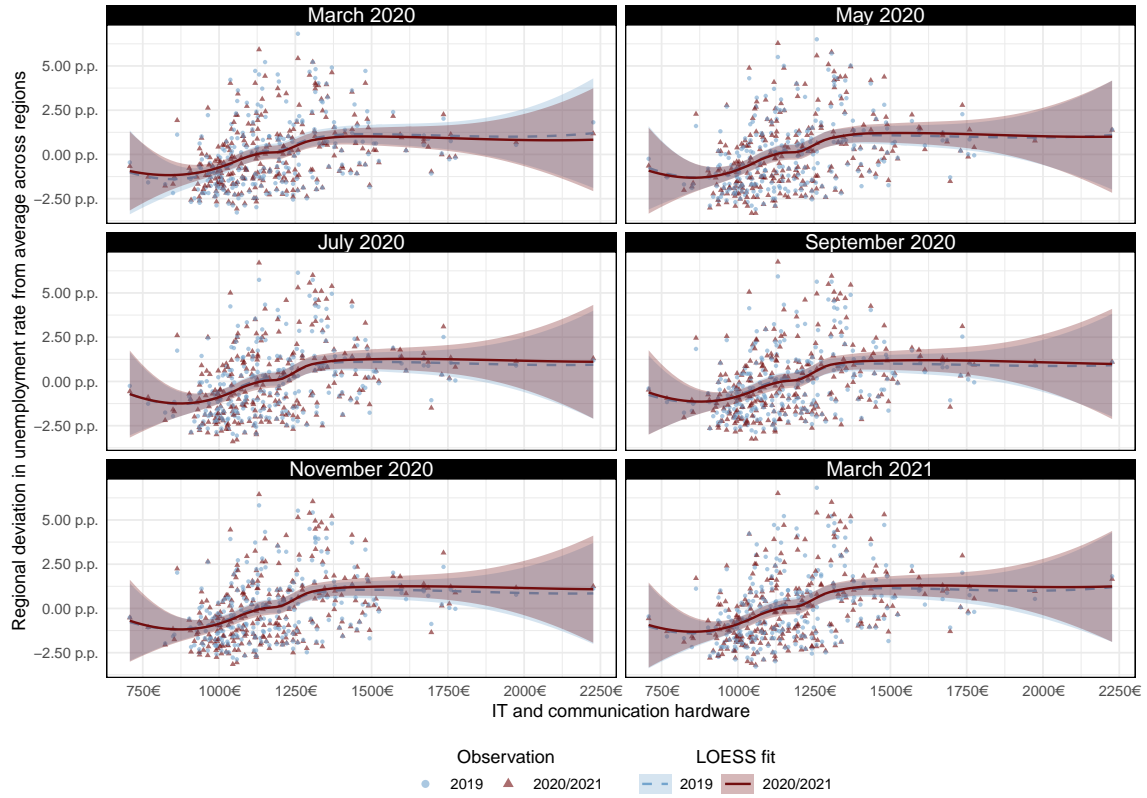
E Unweighted exposure response plots

Figure E1: ICT capital exposure and short-time work rates



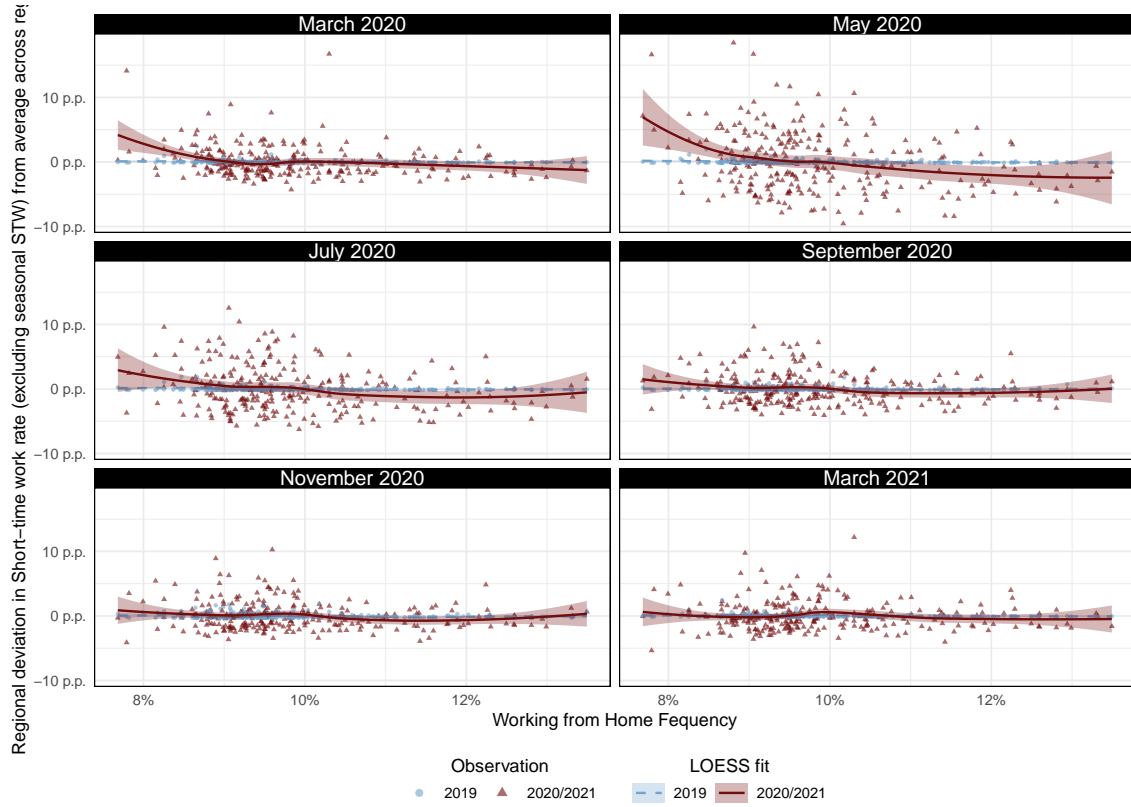
NOTE.- The figure reports deviation in short-time work rates for each 257 labour market regions with respect to the average over all regions. Short-time work rates are calculated as the number of workers using short-time work in a given month over the employment level in June 2019. Regions are ranked by their pre-crisis exposure to digital capital. Compared to the figure in the main text, differences are shown in the raw data without the covariate balancing

Figure E2: ICT capital exposure and unemployment rates



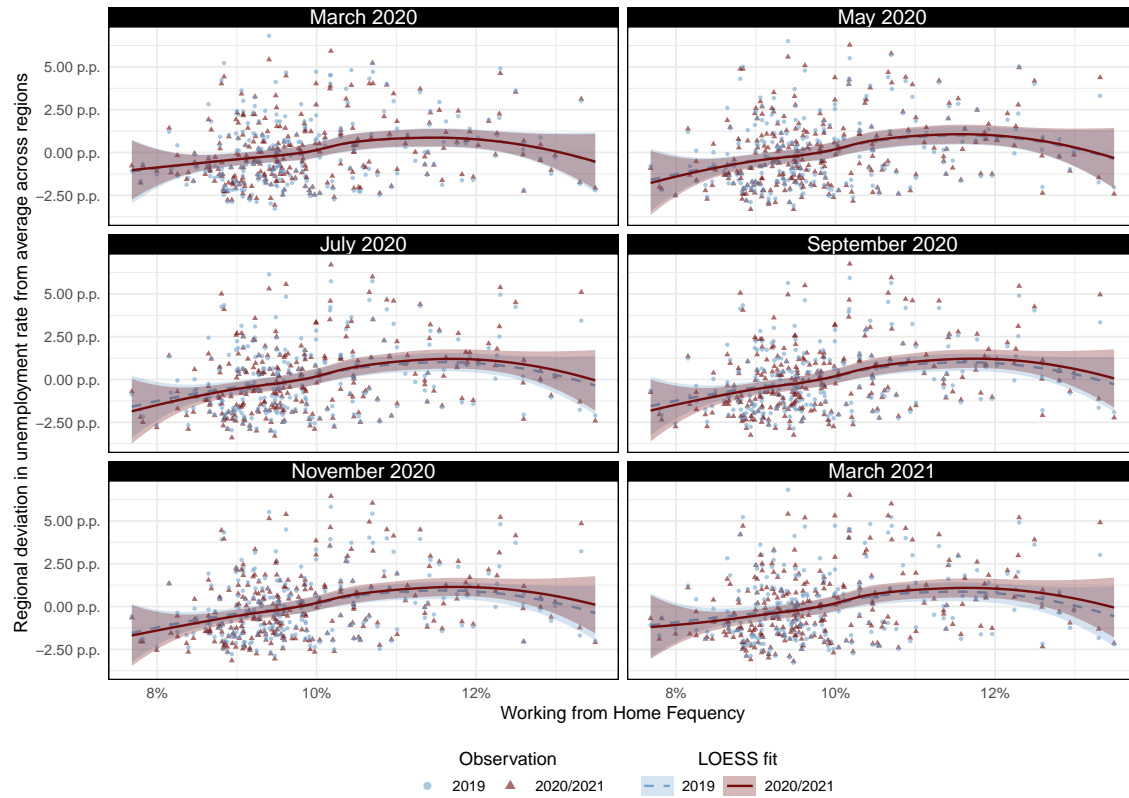
NOTE.- The figure reports deviation in unemployment rates for each 257 labour market regions with respect to the average over all regions. Unemployment rates are calculated as the number of unemployed individuals in a given month over the employment level in June 2019. Regions are ranked by their pre-crisis exposure to digital capital. Compared to the figure in the main text, differences are shown in the raw data without the covariate balancing.

Figure E3: Working-from-home frequency and short-time work rates



NOTE.- The figure reports deviation in short-time work rates for each 257 labour market regions with respect to the average over all regions. short-time work rates are calculated as the number of workers using short-time work in a given month over the employment level in June 2019. Regions are ranked by their pre-crisis working-from-home frequency. Compared to the figure in the main text, differences are shown in the raw data without the covariate balancing.

Figure E4: Working from Home frequency and unemployment rates



NOTE.- The figure reports deviation in unemployment rates for each 257 labour market regions with respect to the average over all regions. Unemployment rates are calculated as the number of unemployed individuals in a given month over the employment level in June 2019. Regions are ranked by their pre-crisis Working from Home frequency. Compared to the figure in the main text, differences are shown in the raw data without the covariate balancing.