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

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ABSTRACT

This article shows 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 digital capital potential higher by one standard deviation led to a short-time work rate that was lower by 1.5 percentage points on average at the onset of the shock. The effect was nonlinear, disproportionately disadvantaging regions at the lower end of the digital capital distribution. We also find that working from home potential led to lower short-time work, especially during the first lockdown period. However, digital capital smoothed the employment shock beyond the effect of remote work, extending into 2021. Moreover, local digital capital potential increased the adoption of remote work after the shock.

JEL Classification: J21, O3, R12, R23

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 (Bai et al. 2021; Bertschek et al. 2019; Comin et al. 2022; Copestake et al. 2024; Doerr et al. 2021), individuals (e.g., Adams-Prassl et al. 2020; Chiou and Tucker 2020) and regions (e.g., Reveiu 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. Through these channels, digital capital likely played a crucial role in managing the sudden and unprecedented labour market downturn during the COVID-19 pandemic. 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).

Digital capital endowments before the crisis, however, varied across regions and firms (Forman et al. 2012; Bellmann et al. 2021). Given this spatial digital divide, it is crucial to understand how it affects regions' capacity to recover from a shock over time. Indeed, local labour market disparities in the response to the COVID-19 crisis were massive. In Germany, relatively few workers lost their jobs at the onset of the pandemic, but many were asked to reduce their working hours under short-time work schemes. Since these schemes were extended in generosity and coverage during the pandemic (Adams-Prassl et al. 2020), they absorbed most of the labour market adjustments.[2] As a result, the share of employees in short-time work spiked to 18% in April 2020. However, this average masked substantial disparities across different local labour markets, with increases ranging from 9 to almost 38 percentage points. In contrast, the unemployment rate only increased to a much smaller extent.

Previous recessions tended to exacerbate regional disparities.[3] Yet, in the case of the pandemic-induced crisis, only a few studies have examined how digital capital or the ability to work from home influenced regional resilience, focusing primarily on the initial employment response during the first 2 months (Alipour et al. 2021; Oikonomou et al. 2023). To the best of our knowledge, however, no empirical study has so far examined how digital capital and remote work affected regional resilience beyond the first lockdown period. This paper aims to fill this gap by analysing how digital capital and remote work helped local labour markets cope with the pandemic crisis in the medium run. We do so for Germany, using detailed administrative data at the county level over the course of more than 3 years.

To identify the causal effects of digitalisation on local employment, we use the latest advances in difference-in-differences techniques to accommodate a continuous treatment. Specifically, the treatment intensity depends on a region's precrisis exposure to digital capital and working from home (WfH). To measure a region's exposure to digital capital, we use precrisis 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. Similarly, to measure a region's WfH potential, we weight precrisis WfH frequency for detailed occupations in Germany by the region's employment shares across these detailed occupations. While these measures are imperfect proxies of local digital capital and WfH usage, they are less affected by potential endogeneity biases than actual regional digital technology adoption. In facts, the latter is likely related to other local characteristics that positively affect labour market resilience.

We then use a propensity score weighting procedure to further disentangle the impact of digital capital and WfH from that of other relevant regional characteristics. This allows us to compare regions with similar 1-digit industry mix, human capital endowment, demographic characteristics, GDP per capita, exposure to other types of capital, as well as several other labour and product market characteristics. Importantly, we show that the digital capital and WfH potential measures are uncorrelated to relevant aspects that shaped the impact of the COVID-19 crisis, such as the employment share in hospitality, tourist stays, global value chain participation and workforce contact intensity. While we cannot completely rule out the possibility that other unobserved, time-varying characteristics are correlated with the two exposure measures and labour market resilience, we argue this threat to identification is minimal given the broad set of covariates considered and strong evidence of parallel trends across the digital capital potential and the WfH potential distributions.

We find that local exposure to digital capital before the pandemic reduced short-time work (STW) usage for more than a year after the shock. An increase in digital capital potential by one standard deviation (around €213 per worker) led to a reduction in STW by 1.5 percentage points (about 9%). However, this average effect conceals significant regional disparities; specifically, regions within the lowest decile of digital capital potential faced STW rates almost 4 percentage points, or roughly 23%, above the overall regional average in Spring 2020. Turning to the effect of remote work, a one standard deviation increase in the WfH potential also led to a 1.5 percentage point (about 9%) decrease in STW rate at the onset of the first lockdown. Unlike the effect of digital capital, the impact of WfH potential on STW was concentrated in the first 3 months following the shock and faded completely after 8 months, even though remote work remained a common practice. Another key difference is that the effect of WfH potential was linear, with similar magnitudes across the WfH potential distribution.

Additionally, controlling for both digital capital and WfH potential in the same regression, we find that digital capital keeps on having a strong and persistent effect. However, the effect of WfH diminishes in both magnitude and precision, suggesting that part of its effect is due to digital capital potential. Exploring the complementary of digital capital and WfH, we do not find evidence that WfH led to stronger reductions in STW in regions with high digital capital potential. But we do find that local digital capital potential increased the adoption of remote work after the shock.

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 remote work (Alipour et al. 2021) in the first 2 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. Confirming earlier results, we find that both digital capital and the spread of remote work made local labour markets more resistant to the shock at its outbreak. However, in the subsequent months and during the second lockdown phase, digital capital gains in relative importance. Second, we explore to what extent digital capital was a pre-condition for remote work 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.

More generally, this paper contributes to the literature analysing the impact of the industrial and occupational structure of regions on their resilience to crises (see, e.g., Martin and Sunley 2020). While previous papers have documented the importance of human capital and the broad industry structure for resilience during the pandemic and earlier recessions (Holl 2018; Partridge et al. 2022), we present evidence that the exposure to digital capital and to work from home - measured using regions' detailed industrial and occupational structure - enhanced regional resilience to the COVID-19 crisis, conditional on workers' educational attainment and the broad industry structure.

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 | Conceptual Framework

2.1 | Regional Labour Markets' Resilience to Economic Shocks

Regional economic resilience has been a growing topic in both economics and geography, in particular since the Great recession of 2007-2009. While the concept varies in definition and focus across disciplines, we concentrate on the ability of regions to resist from a negative shock, the first dimension of resilience as conceptualised in Martin (2012).[4] Regions may differ substantially in their resilience to economic shocks, as shown by the emergence of spatial disparities in the reaction to shocks and the evolution of these disparities over time. For instance, there is evidence from the U.S. that regions hit harder during economic recessions experienced long-term declines in employment and income, leading to a wider spatial employment inequality (Yagan 2019; Hershbein and Stuart 2024).

Given the substantial implications for regional development and regional disparities, it is crucial to understand the key determinants of regional resilience. A large literature has explored several potential factors, such as the industrial structure or labour market conditions (see Martin and Sunley 2020, and references herein). The relative importance of factors influencing the adaptive capacity of regions may depend on the source of the economic shock. There is evidence of a positive correlation between the resilience to the Covid-19 crisis and the resilience to past, and more standard, economic crises, such as the Great recession (Gajewski 2022). This suggests that important resilience factors during previous recessions may have mattered also during the pandemic crisis. However, it is likely that some regional characteristics may have mattered more during the Covid-19 crisis, due to the specificity of a pandemic shock. Given that the outbreak of similar pandemics in the future cannot be ruled out, it is very important to highlight the factors that have been particularly important for resilience during the Covid-19 pandemic.[5]

While the regional industry mix has been important also in previous crises (Brakman et al. 2015; Holl 2018), the Covid-19 pandemic crisis has impacted different sectors and individuals compared to previous recessions, with the largest impact in leisure service sectors such as restaurants, hospitality, and travel (Alon et al. 2022; Partridge 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 (Bauer and Weber 2020; Kong and Prinz 2020). However, there is evidence that the increase in infections led to a drop in local employment even in the absence of lockdown, as shown for South Korea (Aum et al. 2021). In facts, most sectors have been impacted by the crisis in 2020 with few exceptions (Forsythe et al. 2020).

Other factors that have been shown to be important for resilience during the Great recession are the human capital and job-related skills intensity of the regional economy (Crescenzi et al. 2016; Holl 2018; Weinstein and Patrick 2020) and digitalisation (Reveiu et al. 2023). The fact that low-skilled workers have been hit much harder by the crisis provides some evidence that human capital has also been important for resilience during the Covid-19 pandemic. However, especially digitalisation and the ability to work remotely are likely to have played a crucial role during the Covid-19 crisis, as discussed in the next section.

2.2 | The Role of Digital Technologies and Working From Home

Digital technologies have been shown to be an important factor for the resilience to a crisis. Research on previous recessions has documented that ICT-intensive firms were less severely impacted by economic shocks and were more successful in introducing process innovations (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 Great recession. At the regional level, Reveiu et al. (2023) provide evidence that more broad regional measures of digital development also proved to be important for labour market resilience during the Great recession.

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, allowing for a faster reaction to disruptions in supply changes and changes in demand. For instance, it was fundamental for increasing online and contactless 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. Indeed, there is evidence at the firm-level that digitalisation has been even more important for resilience during the pandemic recession than in previous ones (Copestake et al. 2024). Oikonomou et al. (2023) provide some early evidence at the regional level for the US showing that states where firms adopted more ICT even long before the crisis had lower unemployment rate in spring 2020. Based on these arguments and results, we formulate a first hypothesis on the role of regional digital capital endowment for the resilience from the Covid-19 shock:

H1. *Local labour markets with a higher precrisis digital capital endowment are more resilient to the Covid-19 crisis.*

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 44% in Germany in May 2020 (Haas et al. 2021). Several papers have documented how workers in occupations that allow for WfH faced a lower likelihood of losing their job or being in short-time work schemes (Adams-Prassl et al. 2020; Béland et al. 2023).

Evidence shows that WfH impacted regional resistance to the initial Covid-19 shock. In particular, Alipour et al. (2021) show 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. Similar evidence for the US has been found by Oikonomou et al. (2023) on the unemployment response in Spring 2020. While not studied yet, it is likely that WfH mattered also for resilience beyond the first lockdown phase given the further lockdowns and the self-isolation measures implemented in a period where the health risks of the pandemic where still very high. This leads us to formulate our second hypothesis:

H2. *Local labour markets with a higher precrisis working from home usage show a greater resilience from the Covid-19 recession.*

Whether tasks can be efficiently 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. 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. However, 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. 2023; Bellmann et al. 2021; Gathmann et al. 2024; Valero et al. 2021). Because of this, the impact of working from home for resilience is likely to depend at least partly on precrisis digital capital endowments. Oikonomou et al. (2023) find indeed some evidence of a complementary role of digitalisation and remote work potential for resistance to the Covid-19 crisis in the US. Building on these early findings, we formulate our third and last hypothesis:

H3. *Precrisis digital capital endowment and working from home usage are complementary factors for local labour market's resilience to the Covid-19 crisis.*

The importance of technology and working from home during the crisis may also matter for regional disparities. High-income regions with a more educated workforce tend to have invested more in ICT in the past (Forman et al. 2012) and to have a higher working-from-home prevalence before the COVID-19 crisis (Irlacher and Koch 2021). Thus, differences in the precrisis ICT endowments and working-from-home prevalence between richer and poorer regions could potentially lead to an increase in regional disparities in the aftermath of the COVID-19 pandemic recession. Investigating the role of digitalisation and working from home for regional disparities in the aftermath of the Covid-19 pandemic requires a long-run analysis and is beyond the scope of this study. However, the results of this paper are informative for future research on the impact of the Covid-19 crisis on regional disparities, as discussed in Section 6.

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.

Monthly reports on short-time work (STW) 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. The main results use the aggregate county-level STW data. We also employ county-industry level data to decompose and analyse the within-industry responses. In Section A of the appendix, we disentangle the between and within industry variations in regional STW. Moreover, we exclude seasonal STW, used mostly by specific industries in the winter, and focus on business-cycle-related STW, which is more relevant for the COVID-19 crisis.

The employment measures are based on different geographic concepts: unemployment and employment data follow a residence-based approach, while STW and vacancy data use a place-of-work concept, relying on employer-reported job locations. To address inconsistencies between these measures, we aggregate county-level data into 257 labour market regions defined by Kropp and Schwengler (2016) based on commuting patterns. This approach also ensures that economically linked counties with similar industry structures are analysed together, capturing more coherent regional responses to the COVID-19 shock.

3.2 | Employment Responses Across Local Labour Markets

3.2.1 | Regional Variation

Local labour markets had different employment responses, especially at the onset of the pandemic. Figure 1 shows the evolution of STW usage over time for four groups of labour

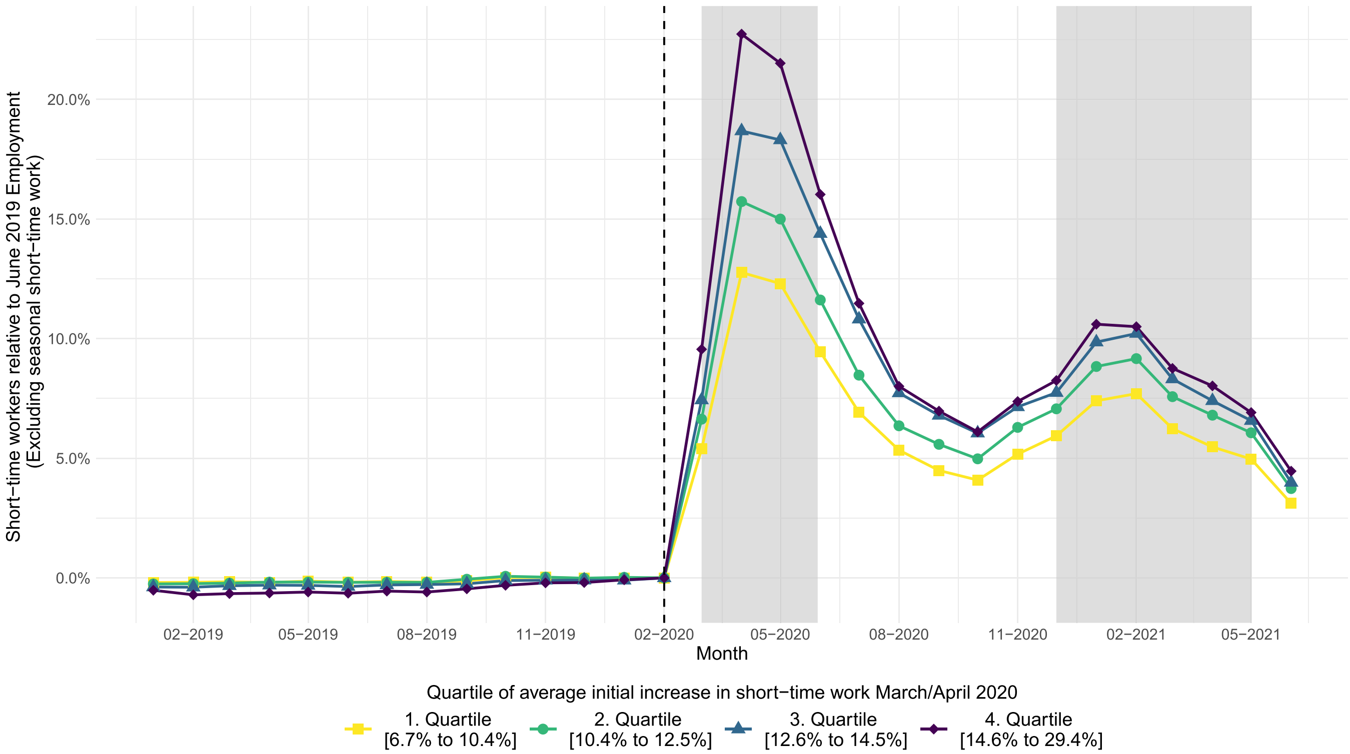

FIGURE 1 | Changes in short-time work across local labour markets. *Note:* The figure depicts the short-time work (STW) rates of regions relative to February 2020 grouped by quartiles of the average increase of STW in March/April relative to the previous year. The periods of the two lockdowns in Germany in spring 2020 and the winter from 2020 to 2021 are marked in grey. STW rates are calculated as the number of workers using STW in business-cycle-related STW in a given month over the employment level in June 2019.

market regions ranked by their initial increase in STW rate. STW rates saw sharp increases in March and April 2020, when differences across local labour markets were as high as 25 percentage points. Even when regions are grouped into four categories, the least affected group had STW rates below 10.4%, while the most affected group saw 29.4% of workers in STW. After the initial increase, STW rates declined until October 2020 when the regional differences had reduced to about 3 percentage points. STW rates increased again during the second lockdown, but regional differences remained stable. About 1 year after the initial shock, STW rates and their regional differences declined further.

In Germany, STW has been the margin of adjustment of labour markets during the COVID-19 crisis. Contrary to STW, 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 A1 in the appendix). Moreover, it was back to precrisis levels in all regions by summer 2021. Given the small response of unemployment, we focus on local STW variation in the rest of the paper.

3.2.2 | The Role of the Local Broad Industry Mix

The effect of the crisis on employment varied greatly across sectors of the economy. The hospitality industry was affected the most. In Appendix A, 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 the broad industry mix. In the rest of the paper, we study how the exposure to digital capital influenced regional differences in STW 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), (ii) controlling for the local employment shares in the 1-digit manufacturing, construction, retail and hospitality industries, and iii) estimating the impact of local digital capital potential on the sector-specific STW rates.

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.[6] Our measure of ICT capital combines computing equipment capital and communications equipment capital. Therefore, it includes 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 data set is that missing data is imputed consistently through an iterative bi-proportional fitting procedure using totals by industry and totals by asset from official sources (Bontadini et al. 2023).

To compute the local exposure to working from home (WfH), we use occupational-level data on WfH 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 WfH 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.

We provide a first description of how STW rates have evolved based on a region's digital capital potential or on its WfH potential. Figure 2 plots the average share of short-time workers across four groups of regions, categorized by quartiles of the local digital capital potential distribution. The figure suggests that regions with higher digital capital experienced a smaller initial shock indicating that digital capital enhanced resistance to the shock. However, all quartiles followed a similar path in recovery. Similarly, Figure 3 plots the average share of short-time workers across four groups of regions, categorized by quartiles of the regional WfH potential distribution. The figure suggests that regions with higher WfH potential experienced a smaller initial shock indicating that WfH enhanced resistance to the shock. However, all quartiles followed a similar path in recovery. The evolution of STW rates in Figures 2 and 3 provide descriptive evidence that digital capital and WfH primarily influenced resistance to the shock, rather than the trajectory of recovery. In the next section, we describe the empirical approach we adopt to identify the effect of digital capital controlling for confounding factors.

3.4 | Other Regional-Level Data

Apart from data on employment, digital capital and WfH, 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.[7] 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.

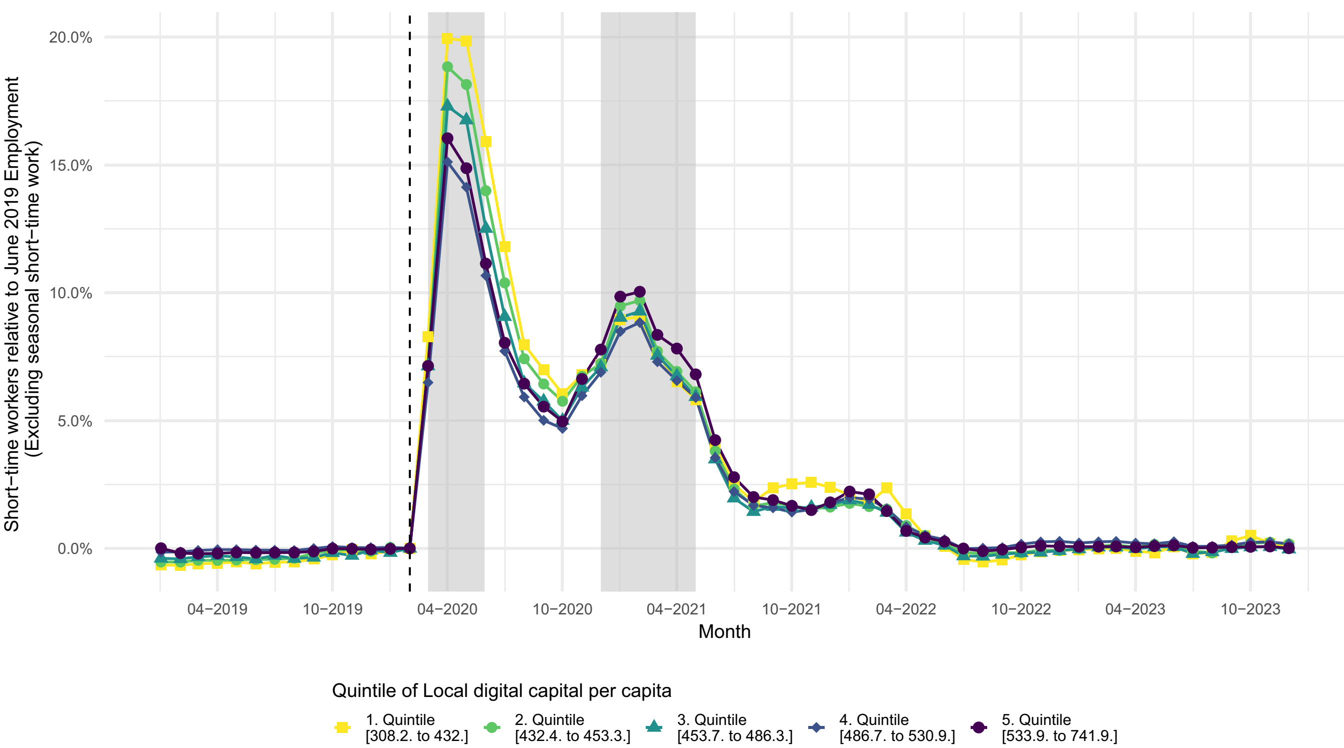

FIGURE 2 | Short-time work rates by regions' digital capital potential. *Note:* The figure plots the share of short-time workers (relative to June 2019 employment) across regions in different quintiles of the per capital digital capital potential. The vertical dashed line marks the onset of the COVID-19 shock. The shaded areas represent lockdown periods.

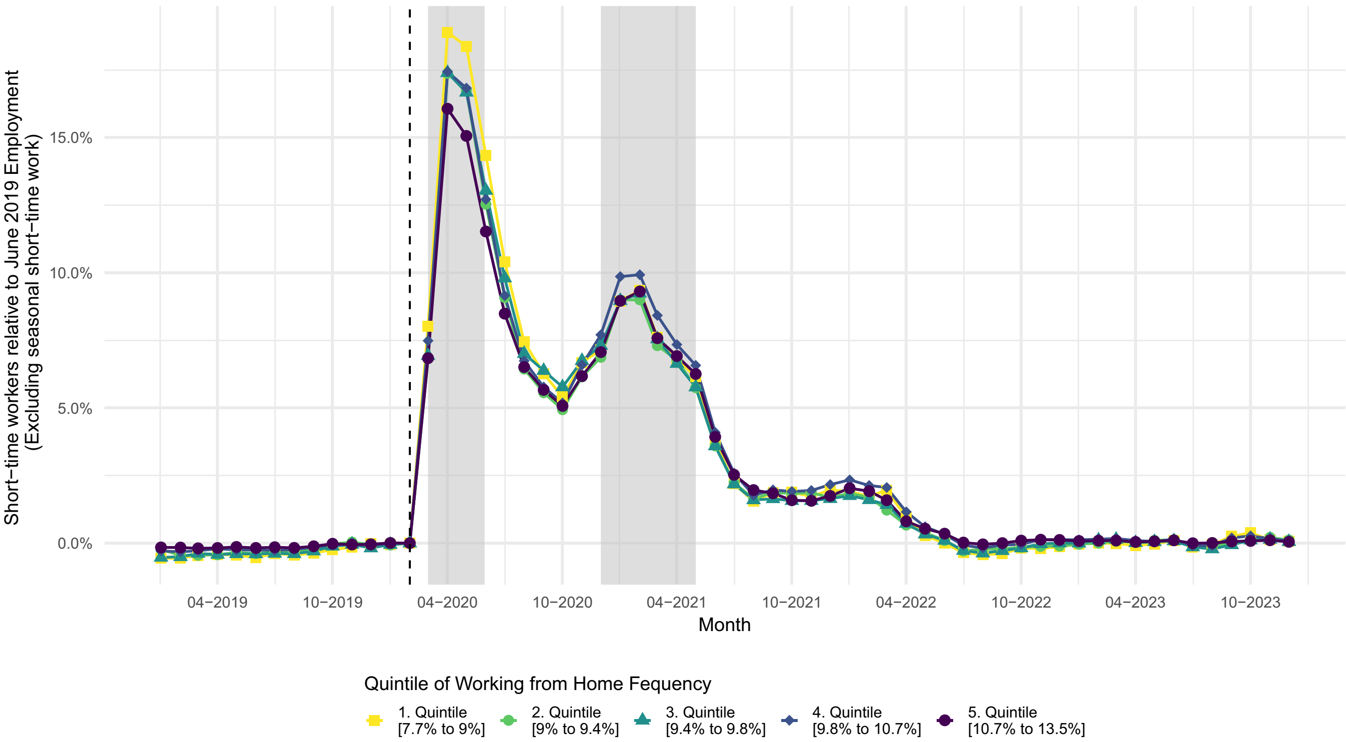

FIGURE 3 | Short-time work rates by regions' working from home potential. *Note:* The figure plots the share of short-time workers (relative to June 2019 employment) across regions in different quintiles of the WfH potential. The vertical dashed line marks the onset of the COVID-19 shock. The shaded areas represent lockdown periods.

4.1.1 | Digital Capital Potential

The measure of local labour market exposure to digital capital uses precrisis (2019) data on employment at the county and industry level and data on ICT capital at the national and industry level.[8] 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 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 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 4a 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.

4.1.2 | Working From Home Potential

The local WfH potential is based on data on actual remote work 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 precrisis 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:

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

Figure 4b shows that local labour markets vary in their WfH 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

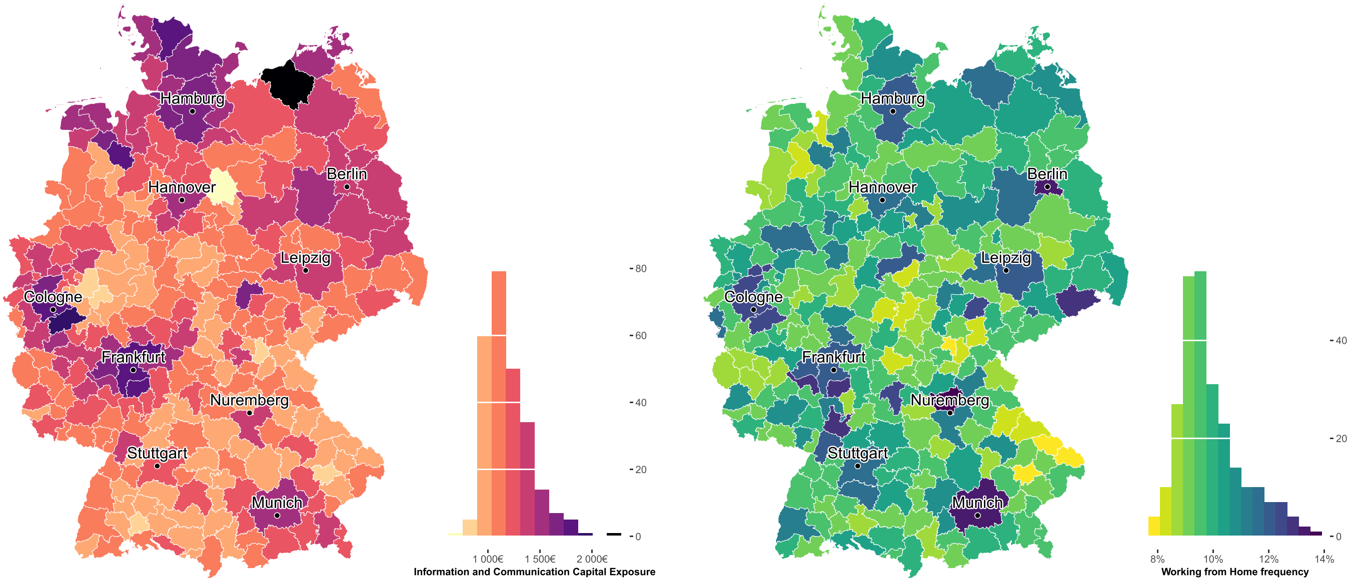

FIGURE 4 | Maps of digital capital and working from home potential across local labour markets. *Note:* Map (a) shows the average precrisis local digital capital potential per capita as constructed as in Equation (1). Map (b) shows the average precrisis local WfH potential as constructed as in Equation (2) for all 257 labour market regions.

and Erlangen, with jobs in 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 WfH potential.[9] The strategy then allows to identify the effects of local exposure to digitalisation and to WfH on short-time work (STW) and unemployment rates by making local labour markets comparable through the weighting approach.[10]

4.2.1 | Main Assumptions

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

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. (2024). 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 STW for regions with different intensities of digital capital or WfH potential before the COVID-19 outbreak (see the first row of Table 1, and Table 2. Figure B1 presents a nonparametric estimation of the effect along the full continuous distribution of digital capital. The graphs before March 2020 provide further evidence supporting the strong parallel trend assumption, since the effect on STW is flat at zero across the whole distribution for the pre-periods.

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 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 Figures 5 and B2).

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 midterm 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.

4.2.2 | Inverse Probability Weighting

To disentangle the impact of digital capital and WfH potential from that of other relevant regional characteristics, we use an inverse probability weighting strategy 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 B.

We apply separate weighting procedures for digital capital and WfH potential, but include the same covariates in both. As control variables, we use detailed information on the industry structure, such as the employment share of 1-digit industries (manufacturing, construction, retail, hospitality) and the share of jobs in essential industries during the pandemic to 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 of 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.[11] Since firms and industries in some regions might be more used to the procedures related to short-time work, we include the peak in the STW 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 STW, we also include the share of firms with more than 250 employees. Lastly, 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 5.

Figure 5 shows that the weighting method helps to achieve a very good balance of all targeted characteristics both along the digital capital and WfH potential distribution. In the left panel of Figure 5, the unweighted results showed by the blue squares reveal 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 right panel shows that the WfH potential has very high correlation (above 0.9) with the share of college educated workers. However, after weighting, as shown by the red triangles, the balance along key covariates is extremely good for both variables of interest. The correlations in the generated pseudo-samples are always below 0.15 for all variables included in the weighting approach.

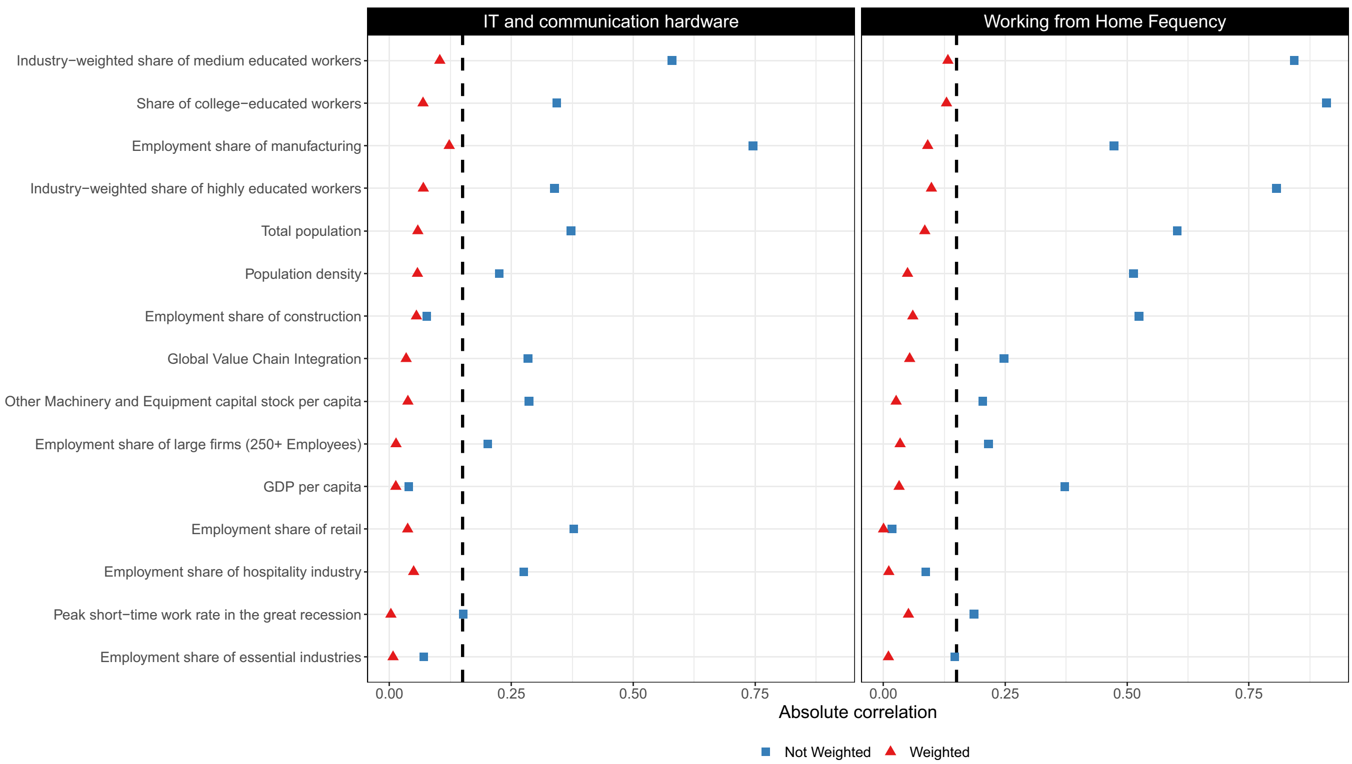

FIGURE 5 | Balance plots for targeted covariates. *Note:* The left panel shows the absolute correlations between the targeted covariates and local digital capital potential in both the weighted (red triangles) and the unweighted sample (blue squares). The right panel shows the absolute correlations between the same covariates and local working from home potential.

In addition to improving the balance of targeted characteristics, the weighting procedure also achieves balance across several important nontargeted dimensions, as shown in Figure B2 of the appendix. After weighting, the correlations with both digital capital and WfH potential are consistently below 0.15 for all key variables reported in the figure. In particular, given that the pandemic led to a "she-cession" in many countries, we show that after re-weighting regions exhibit similar female employment and part-time employment shares.[12] 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. While we cannot completely rule out the possibility that unobserved, time-varying characteristics are correlated with the exposure measures and employment resilience, we argue that threats to the conditional independence assumption are minimal given the similarity of regions in a broad set of covariates.

Finally, to ensure common support, we first trim the 5% of regions with the highest and lowest weights. Second, we show that there are many regions at different values of the treatment in the adjusted sample (see Figure B3 for digital capital and Figure B4 for WfH potential in the appendix).

4.2.3 | 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:

$$Y_{rt} = \sum_{t=-12,t\neq 0}^{T} \beta_t \text{Digitalisation}_r \times \text{Time}_t + \sum_{t=-12,t\neq 0}^{T} \gamma_t \text{Time}_t + \alpha_r + \varepsilon_{rt}. \quad (3)$$

where Y_{rt} is either the STW rate (i.e. the number of workers using STW 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.[13] 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 24 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 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). In the event-study approach, we cluster standard errors by region to account for potential spatial correlation in labour market outcomes within local labour markets.

5 | Results

5.1 | Digital Capital

We start by analysing how regions' precrisis exposure to digital capital impacted their labour market performance during the COVID-19 crisis. We first look at the short-time work (STW) 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.

5.1.1 | 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 STW 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 1 standard deviation increase in digital capital, that is 213€ per worker, on STW, in each month relative to February 2020. Figure 6 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 STW rates before 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 STW. In April and May 2020, one-standard-deviation increase in digital capital corresponded to a 1.5 percentage point (pp) reduction in the STW rate. Given that the STW rate rose by 20 pp 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 STW schemes to a lower extent.

5.1.2 | Heterogeneous Effects Across the Regional Distribution

How does the impact of digital capital exposure on STW rates vary across its regional distribution? Table 1 shows that the results are strongest for the bottom of the digital capital distribution. Column 1 reports similar results to those in Figure 6 where 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 for high local digital capital, defined using various cut-off 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, STW rates were nearly 4 pp lower in regions in the top nine deciles compared to those in the bottom decile, while they were 2.5 pp 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 smaller in magnitude (see column 5). However, the impact appears to be longer lasting using the median cut-off, with an impact of 0.7 pp for the period between November 2020 and June 2021 and of 0.4 pp for the period between November 2021 and February 2022 (statistically significant at the 10% level). When using cut-off points above the median, the impact of digital capital becomes small and barely significant

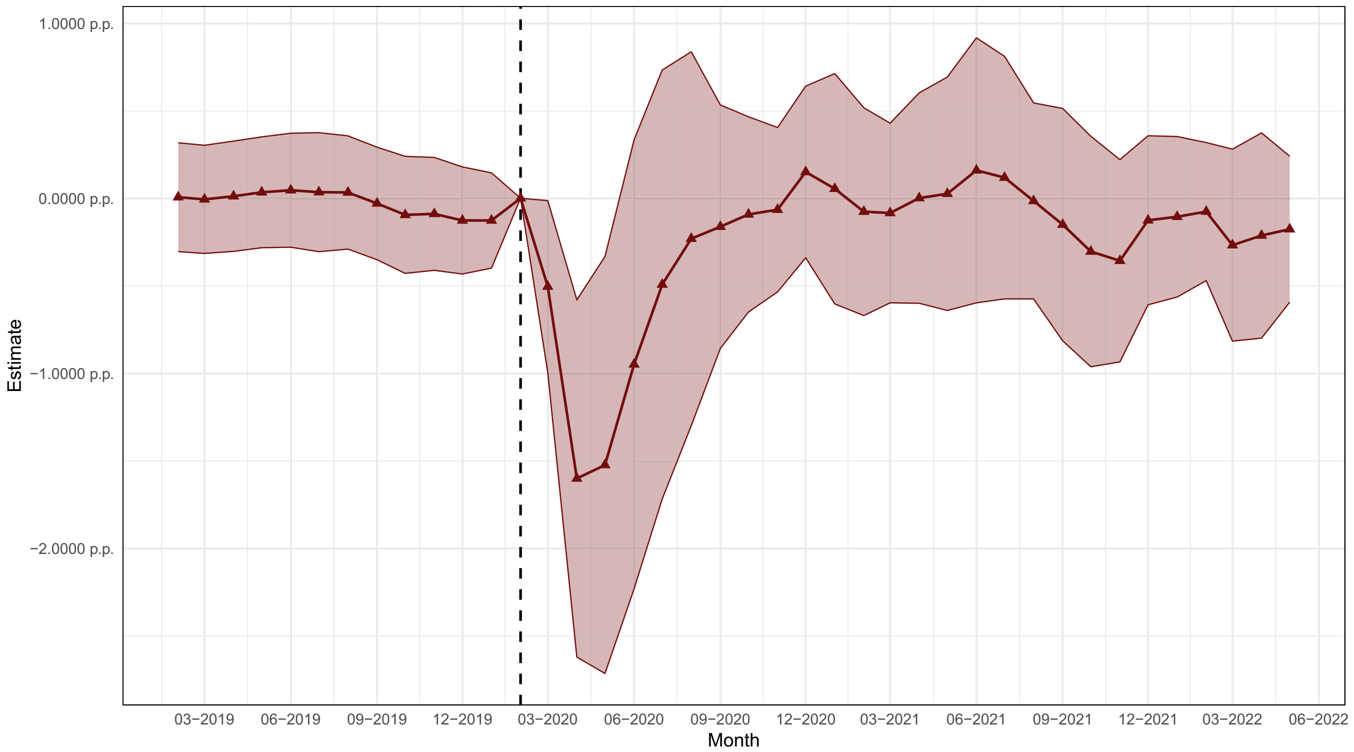

FIGURE 6 | Event-study estimates of digital capital on short-time work rates. *Note:* The estimates measure the change in short-time work rates relative to February 2020 for a standard deviation increase in ICT capital. Short-time work rates are calculated as the number of workers using short-time work in a given month divided by the employment level in June 2019. The figure displays the 95% confidence intervals with the main estimate. Standard errors are clustered at the local labour market level.

for any time period considered (see columns 7 and 8). Notably, the coefficients for the period before February 2020 are small and insignificant in all specifications, confirming the validity of the strong parallel trends assumption. This is confirmed by Figure B1 in the appendix which presents a non-parametric estimation of the effect along the full continuous distribution of digital capital. 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 STW schemes especially during 2020.

5.1.3 | Short-Time Work Within Broad Industries

The effect of local exposure to digital capital on aggregated local STW can be decomposed into its impact within five broad industries. We estimate the event study specification from Equation 3 employing the sector-specific STW rate and keeping the same digital capital measure as in the main model. A differential impact by sector may stem from differences in the levels of digital capital in detailed industries within the broad sector considered or by spillover effects due to higher digitalisation in other sectors, such as the IT and other information services sector. Figure C1 in the appendix shows that higher digital capital helped protect employment in almost all industries with the exception of the construction sector. The largest effects are observed within manufacturing where a 1 standard deviation increase in digital capital potential led to a reduction in STW of about 5 pp during the first 3 months following the initial shock, with effects persisting above 1 pp for up to 8 months. This analysis also shows that the role of digital capital was most persistent in the hospitality sector, and especially pronounced during the lockdowns. In that sector, a 1 standard deviation increase in digital capital potential remained associated with a reduction in STW of more than 2.5 pp 1 year after the initial shock.

5.1.4 | Resistance and Recovery

Figure 2 in Section 3 shows descriptively that higher digital capital is not correlated with a quicker recovery despite being associated with a lower initial shock. To further address the role of digital capital for the length of recovery, Figure C2 plots the time to recovery against digital capital per capita on the weighted sample of regions. The results confirm that higher digital capital does not appear to be associated with a faster return to pre-pandemic employment levels. Instead, most regions returned to precrisis STW levels between June and July 2022. Thus, digital capital affected regional resistance but did not speed up the recovery from the shock. This may be explained by the fact that firms in lagging regions could have rapidly invested in digital capital to recover from the shock, as the differences in digital capital per worker across regions were below €1,000.

5.1.5 | Unemployment Rate

One question that arises from the STW results is whether regions with low digital capital endowments also experienced

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)
November 2020 to February 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)
July to October 2021	−0.088	−0.587	−0.085	−0.135	−0.359	−0.249	−0.113	−0.295
	(0.318)	(0.530)	(0.259)	(0.224)	(0.328)	(0.270)	(0.290)	(1.059)
November 2021 to February 2022	−0.167	0.024	−0.206	−0.080	−0.207	−0.387*	−0.035	−0.437
	(0.230)	(0.395)	(0.249)	(0.207)	(0.272)	(0.228)	(0.251)	(0.713)
Time-fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Region-fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
N	7710	7710	7710	7710	7710	7710	7710	7710
Adjusted R^2	0.77	0.77	0.77	0.77	0.77	0.77	0.77	0.77

Note: This table presents estimates of the difference-in-differences specification 3 with alternative definitions 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). Robust standard errors clustered at the local labour market level are reported in parenthesis. Significance level: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

higher unemployment increases or whether STW schemes and job mobility prevented unemployment increases in low digital regions. Figure C3 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 STW 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 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. (2025).

5.2 | Working From Home Potential

One channel through which digitalisation 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 precrisis experience in using such remote work arrangements. We thus investigate whether regions with a higher precrisis exposure to working from home (WfH) benefitted in terms of lower STW and unemployment rates after the Covid-19 outbreak.

5.2.1 | Short-Time Work Rate

As for digital capital, we start by presenting the average results on STW rates for the event-study regression described in Equation (3). Figure 7 shows that WfH potential had no impact on short-time work before the pandemic, confirming the parallel trends assumption. The impact of WfH potential on STW 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.

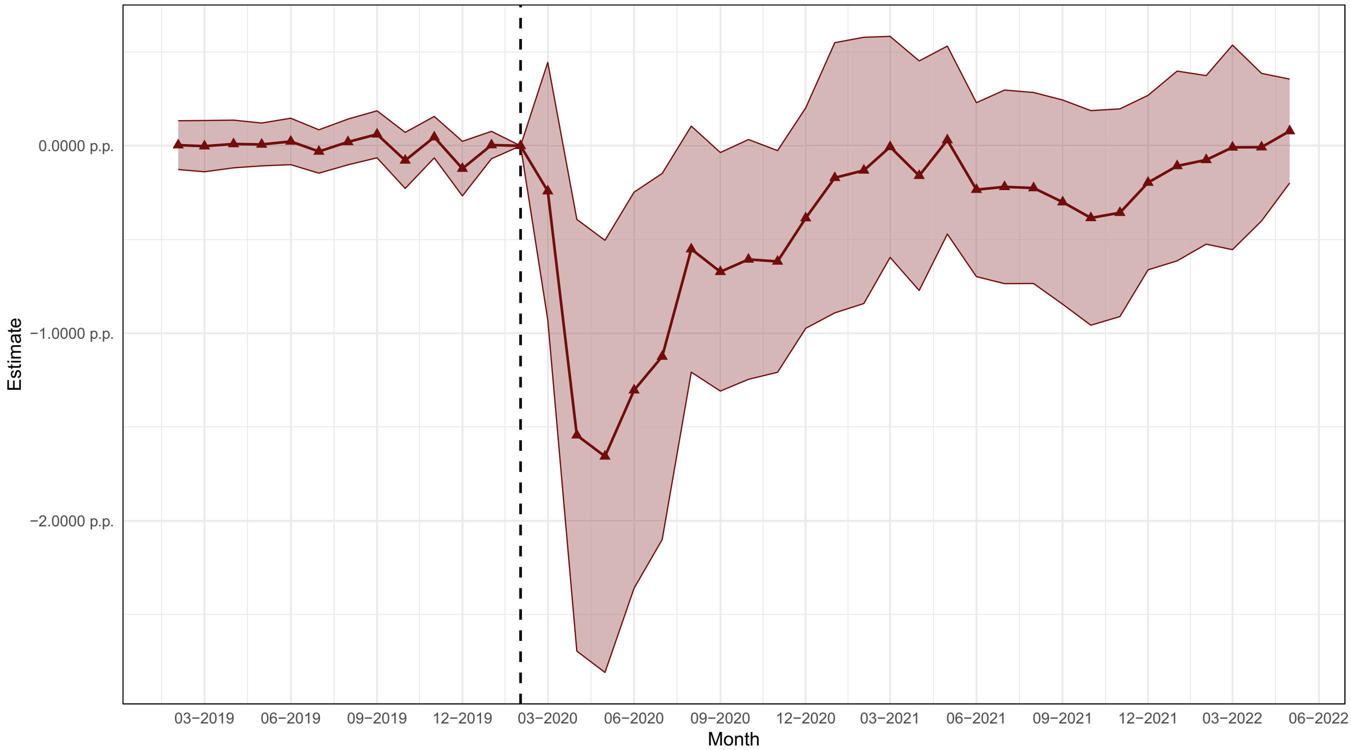

FIGURE 7 | Event-study estimates for working from home potential on short-time work rates. *Note:* The estimates measure the change in short-time work rates relative to February 2020 for a standard deviation increase in WfH potential. Short-time work rates are calculated as the number of workers using 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. Standard errors are clustered at the local labour market level.

When looking at the results over the whole distribution of WfH potential in Table 2, 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.

5.2.2 | Unemployment Rate

Lastly, Figure C3 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 pp between regions with a 1 standard deviation difference in WfH potential.

5.3 | Complementarity or Independence of Digital Capital and Working From Home?

We have shown that both digital capital and WfH reduced the short-time work rate during the pandemic. On the one hand, digital capital and WfH 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. On the other hand, WfH in many jobs may have been feasible with minimal digital capital investment, while digital capital may have contributed to regional resilience beyond enabling remote work, for example, by facilitating online sales (Comin et al. 2022).

To test the hypotheses of complementarity and independence of the two measures, we conduct three exercises. To test for evidence of complementarity, we first examine the relationship between pre-pandemic digital capital and actual WfH usage during the pandemic. Second, we estimate the impact of WfH across regions with low and high digital capital potential. Third, to test the hypothesis of independence, we examine how the coefficients change when we include the measures digital capital and WfH 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 8.[14] 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 8.[15] This suggests that digital capital endowment was necessary for individuals to effectively work remotely during the pandemic even in regions with a higher previous exposure to this working practice. This finding suggests potential complementarity between digital capital and WfH. In the analysis below, we test for complementarity in maintaining employment during the pandemic.

TABLE 2 | 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)
November 2020 to February 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)
July to October 2021	−0.283	−0.052	0.158	−0.173	−0.392	0.021	−0.510	−0.306
	(0.263)	(0.399)	(0.283)	(0.329)	(0.402)	(0.346)	(0.375)	(0.297)
November 2021 to February 2022	−0.184	0.205	0.095	−0.016	−0.029	0.317	−0.273	−0.413
	(0.233)	(0.284)	(0.289)	(0.316)	(0.305)	(0.302)	(0.393)	(0.257)
Time-fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Region-fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
N	7710	7710	7710	7710	7710	7710	7710	7710
Adjusted R^2	0.76	0.76	0.76	0.76	0.76	0.76	0.76	0.76

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 of local WfH potential to estimate linear effects. To estimate the effect of WfH potential along its distribution, we compute dichotomous variables equal to 1 if local WfH is greater than the pth percentile in columns (2) to (8). Robust standard errors clustered at the local labour market level are reported in parenthesis. Significance level:
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

In the second exercise, we split the sample by low and high regional digital capital potential and re-estimate the effect of WfH potential on STW within these sub-samples. Figure C4 displays the results using either the 20th percentile or the 50th percentile as cut-off. It shows that working form home mattered both among the 80% of regions with higher digital capital potential and among the 50% of regions with the lowest one. The fact that we do not find a significant impact on the regions in the lowest quintile of digital capital potential may be due to the small sample (51 labour market regions). Even at different cut-off points, we do not find strong evidence of a systematically larger effect of WfH potential in high digital capital regions.

These two exercises suggest that although digital capital supported the adoption of remote work, it did not enhance its effectiveness in reducing STW take-up—indicating no complementarity between the two in enhancing crisis resilience. In the third exercise, we test whether the two measures have an independent effect on STW by adding them in the same event study specification. We first add the measure of WfH in the event study specification for digital capital to analyse how the estimated coefficients differ compared to the results of Figure 6. This is shown in the left panel of Figure C5 in the appendix, which is very similar to the main specification. Thus, the impact of digital capital does not seem to be driven by WfH. We then add the measure of digital capital in the event study specification for WfH. The right panel of Figure C5 shows that estimated impact of working form home potential appears to be slightly smaller than in Figure 7. The estimate for April and May 2020 is of 1 pp compared to 1.5 pp in the previous specification but it remains statistically significant in this initial period. While this suggests that at least part of the negative impact of WfH potential on STW is due to a higher digital capital endowment, remote work seems to also have an effect on STW independently of our measure of digital capital, at least during the first pandemic lockdown.

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

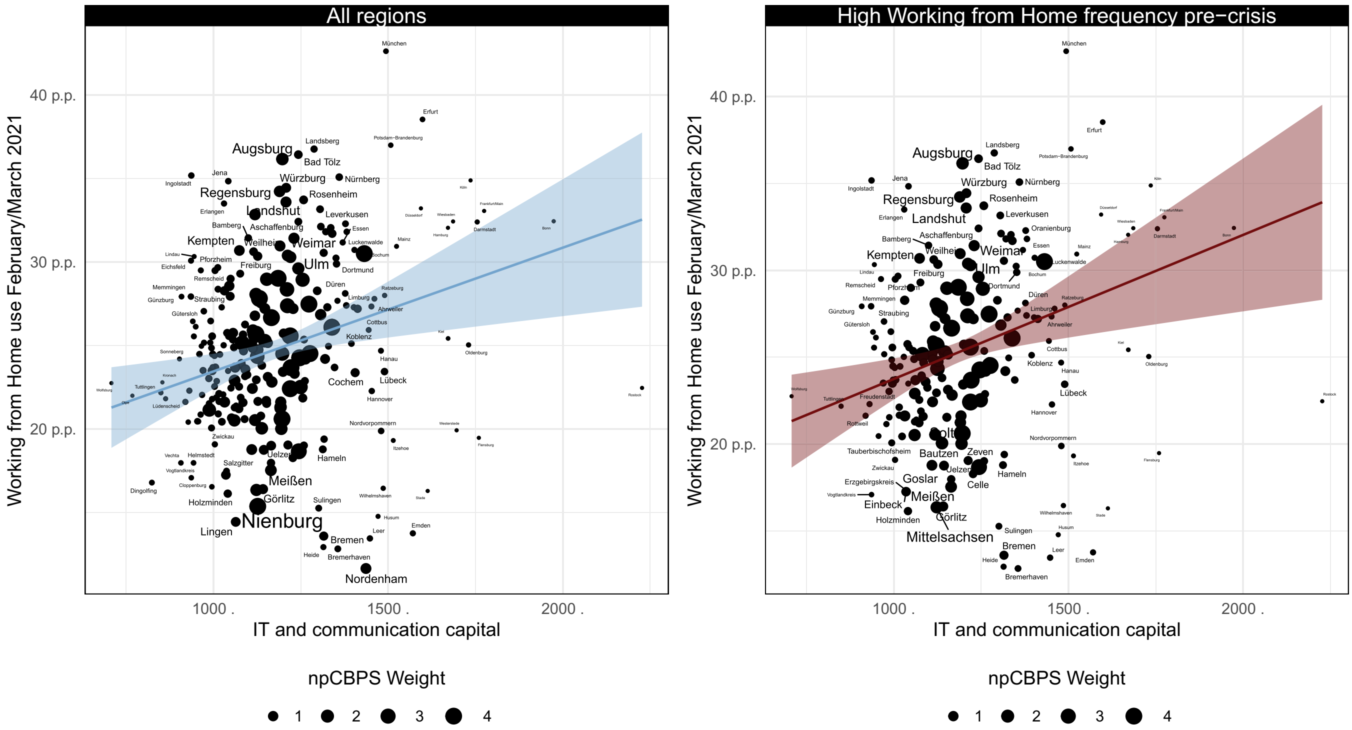

FIGURE 8 | Actual postcrisis working from home usage and precrisis digital capital. *Note:* The figure reports the share of individuals regularly working from home in labour market regions ordered by their level of digital capital per worker. The left panel with a blue line shows the correlation for 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 precrisis WfH potential, i.e. a high share of jobs that can be done from home according to precrisis occupational structure. The size of the dots is proportional to the non-parametric covariate balancing generalised propensity score (npCBPS) weight. Data on actual usage of remote work in March 2021 comes from the Federal Employment Agency.

firms, enabling them to more effectively minimise sick leave and maintain production. We do find that working from home was associated with lower short-time work rates, particularly during the initial months of the pandemic when strict contact restrictions were in effect. Digital capital had a larger and longer-lasting effect on employment than working from home potential, particularly at the bottom of the regional distribution. Moreover, the effect of digital capital remains large and significant even after controlling for working from home potential in the same regression. 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. This suggests that digital capital played a substantial role in enhancing labour market resilience during the crisis, even beyond facilitating remote work. In this light, decision-makers can prioritise investments in digital infrastructure and capabilities, particularly in sectors and localities where such capital is currently lacking. They can also target and support firm creation and firm growth in ICT-intensive industries within broad sectors to strengthen labour market resilience.

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.[16] 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 effect of ICT capital outside strict lockdown periods (see Table 1) suggests that broader, non-COVID-specific mechanisms were also at play.

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 kept its predictive power in the hospitality sector where disruptions persisted. Second, regions lagging behind at the start of the pandemic could have caught up by late 2020, potentially contributing to the fading impact of digital capital thereafter. 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. (2024) 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. 2025).

7 | Conclusion

This article examines the impact of digitalisation and working from home on local labour markets resilience to the pandemic-induced shock in Germany, over a period including both the initial resistance phase and the recovery. While the share of employees in short-time work spiked to 18% at the beginning of the pandemic, local labour markets experienced very different responses, with differences in short-time work rates increases exceeding 30 percentage points. Regional differences attenuated but persisted during the recovery phase.

Our analysis delves into the influence of precrisis levels of digitalisation on the varying regional effects, using metrics related to the potential for digital technology adoption and for remote work adoption. 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. We use similarly computed measure for working from home. To identify the effect of digitalisation on the resilience of labour markets, we adopt a difference-in-differences strategy with a continuous treatment. We show evidence supporting the strong parallel trend assumption. While we cannot completely rule out the possibility that unobserved, time-varying characteristics are correlated with the exposure measures and labour market resilience, we argue that threats to the conditional independence assumption are minimal, given the similarity of regions in a broad set of covariates.

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 higher working from home potential also led to a reduced usage of short-time work schemes, but mostly during the first lockdown. We find a significant impact of digital capital potential also conditional on our working from home measure, and outside of lockdown period, suggesting that other channels mattered as well.

Moreover, we show for the first time that the effect of digital capital on a labour market's resilience is nonlinear. During the COVID-19 pandemic, it was 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 economic shocks should therefore focus on digital capital investment and firm creation in digitally intensive sectors within lagging regions, thereby helping to reduce 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 digital capital adoption and the spatial digital divide postcrisis as more data become available. In particular, data on firms' digital investments and individuals' digital skills at the local level would facilitate investigating how the spatial digital divide has evolved since the crisis as well as its broader implications for economic inequality.

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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.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Endnotes

[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.

[3]See for example Yagan (2019); Hershbein and Kahn (2018); Hershbein and Stuart (2024).

[4]In Martin (2012)'s framework, the resilience is composed of four stages, after the resistance come the *recovery*, *reorientation* and *renewal*. While not the main focus of the paper, we analyse time to recovery by digital capital potential in a separate analysis. Moreover, we will hint at one aspect of the reorientation of labour markets after the pandemic by describing how pre-shock digital capital potential encouraged the adoption of new remote work arrangements. However, an in-depth analysis of the final stages of labour markets' resilience would require longer-term data and warrant another paper.

[5]Focusing on shocks due to past pandemics, evidence has shown that they increased inequality within space, and that socioeconomic conditions, institutional settings, and social policies influenced the resilience of local labour markets (Furceri et al. 2022; Ma et al. 2020).

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

[7]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.

[8]The list of 40 industries is given in Table A1 in the appendix.

[9]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).

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

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

[12]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).

[13]We divide the local number of STW users or unemployed people by local pre-pandemic employment (June 2019) to create comparable rates. Using the same baseline across regions isolates changes in STW from employment fluctuations, ensuring comparability over time and across regions.

[14]Regional-level data on actual WfH adoption is not available for 2020 and only becomes available starting in 2021.

[15]We formally tested for the difference in the share of remote work in February/March 2021 by precrisis WfH potential for low and high IT capital regions by running a OLS specification including a high IT capital dummy, the precrisis WfH potential and their interaction. We found that the interaction is statistically significant confirming complementarity. Results are available upon request.

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

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Appendix A

Data and descriptive statistics

Figure A1 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 precrisis 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.

Table A1

A.1 | 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 A2 shows that the hospitality industry was affected the most with more than 30% of its precrisis 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 precrisis 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.

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 by regional differences in short-time work rates within sectors. These within sector differences across regions 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:

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

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:

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

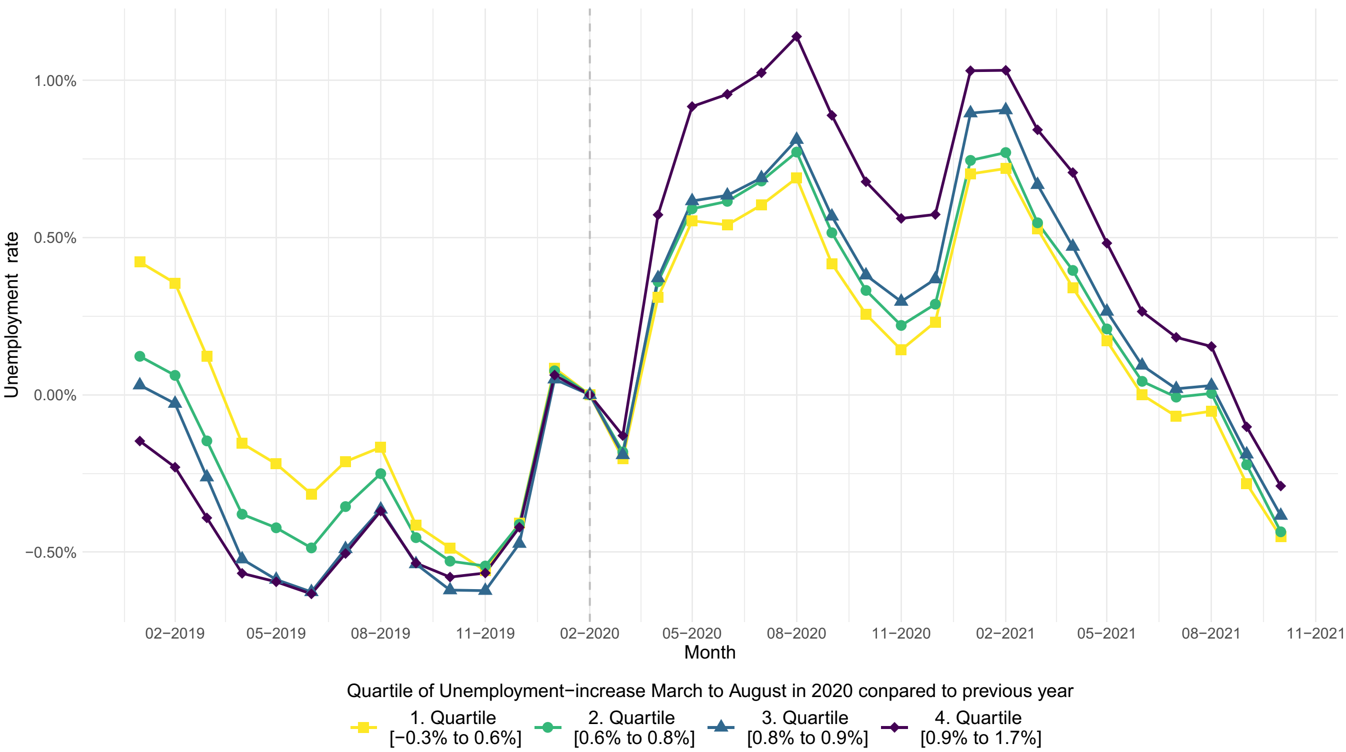

FIGURE A1 | Changes in unemployment across local labour markets. *Note:* The figure shows the evolution of unemployment rates relative to February 2020 grouped by quartiles of the average increase of unemployment between March and August 2020 compared to the same time period in 2019.

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.

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 A3 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.

Appendix B

Empirical strategy

Figure B1

B.1 | 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. $w_i = \frac{f(T_i)}{f(T_i \mid X_i)}$, 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

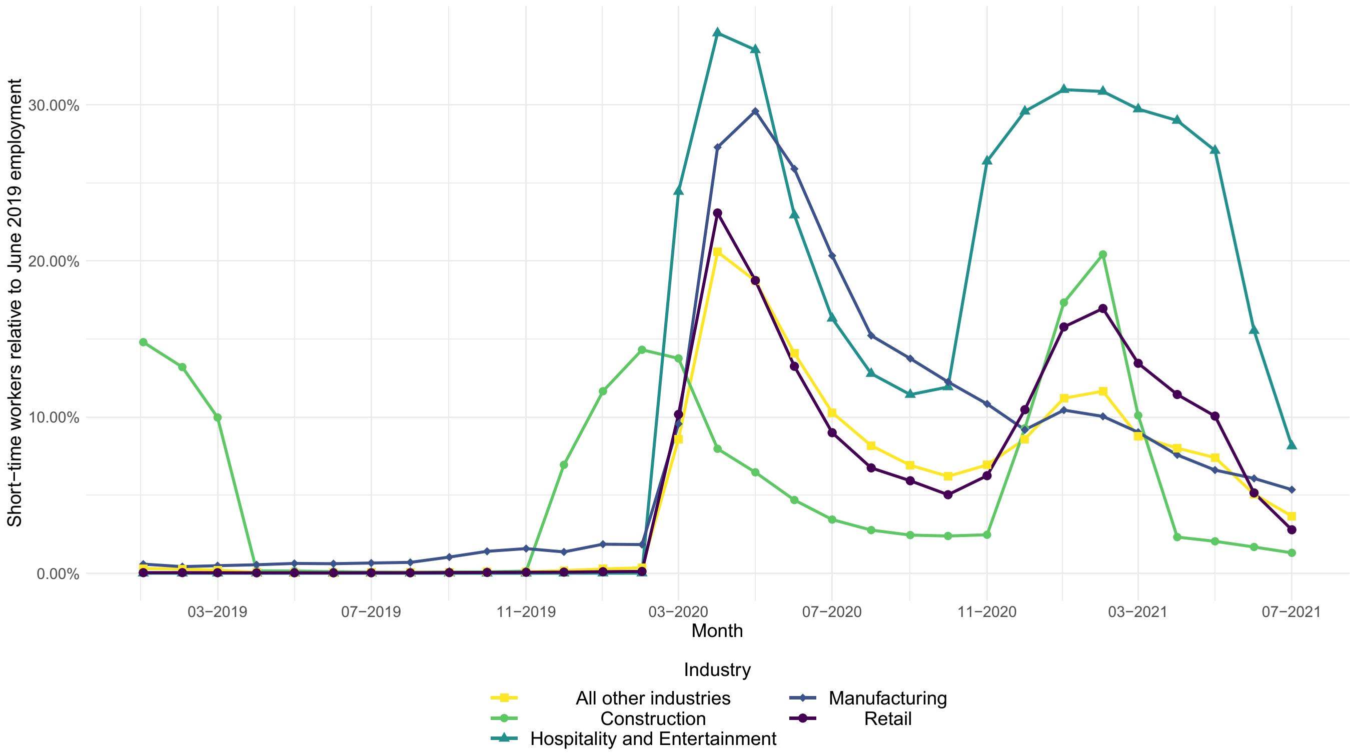

FIGURE A2 | short-time work rates by industries. *Note:* The figure shows the national industry-specific short-time work rates for 5 industries. This level of aggregation allows us to observe these same industries at the level of local labour markets. In contrast to our other results the figure shows the overall short-time work rate including seasonal short-time work while all other figures report business-cycle related short-time work.

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 B2

Figure B3 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 B4 gauges the common support assumption for the regression using WfH potential.

Appendix C

Other results

Figure C1

Figure C2

Figure C3

Figure C4

Figure C5

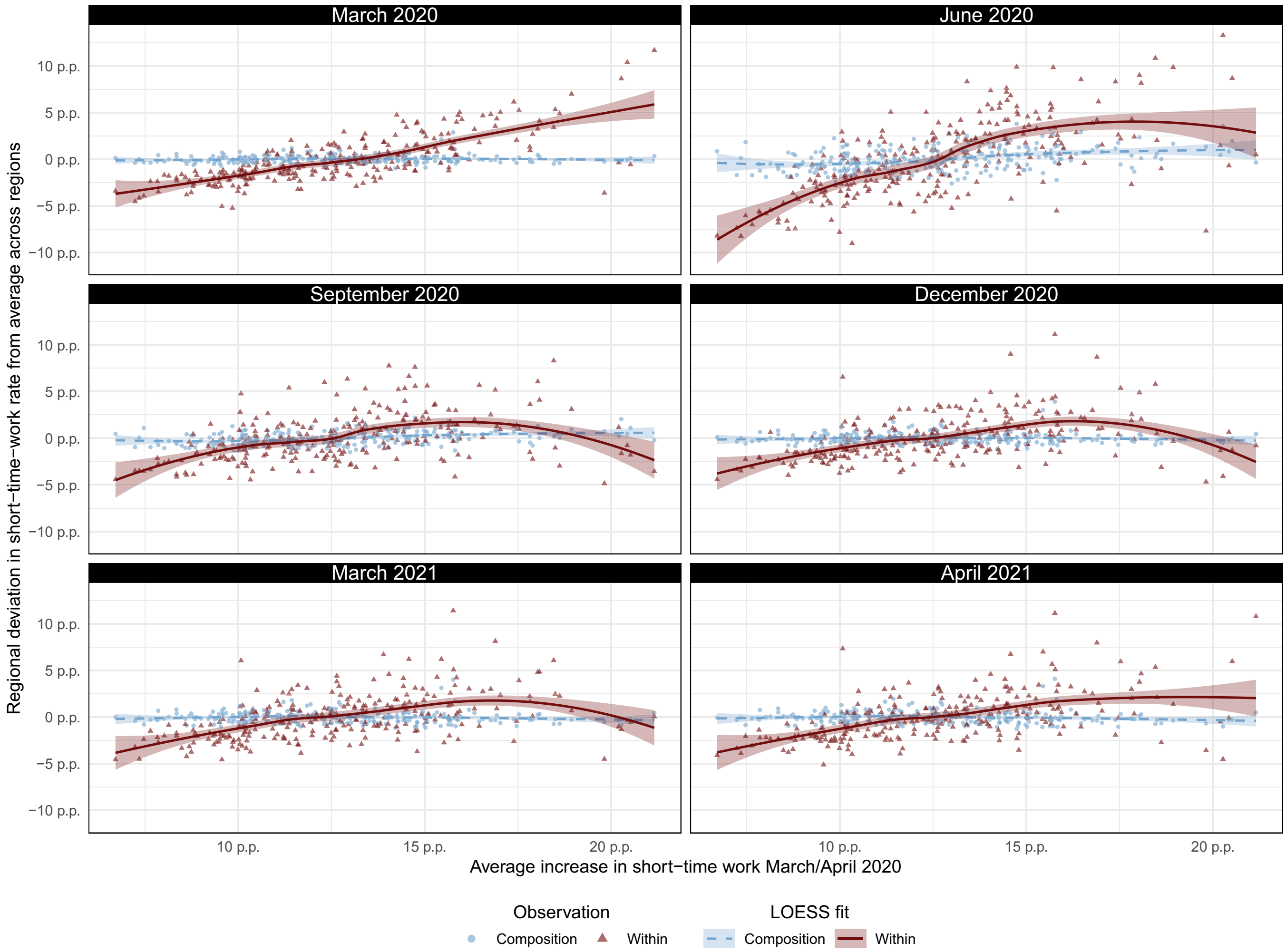

FIGURE A3 | Decomposition of regional short-time work rates into industry-composition and within-industry components. *Note:* The figure reports deviations in short-time work rates for each 257 labour market regions with respect to the average over all regions. Regions are ranked by their short-time 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.

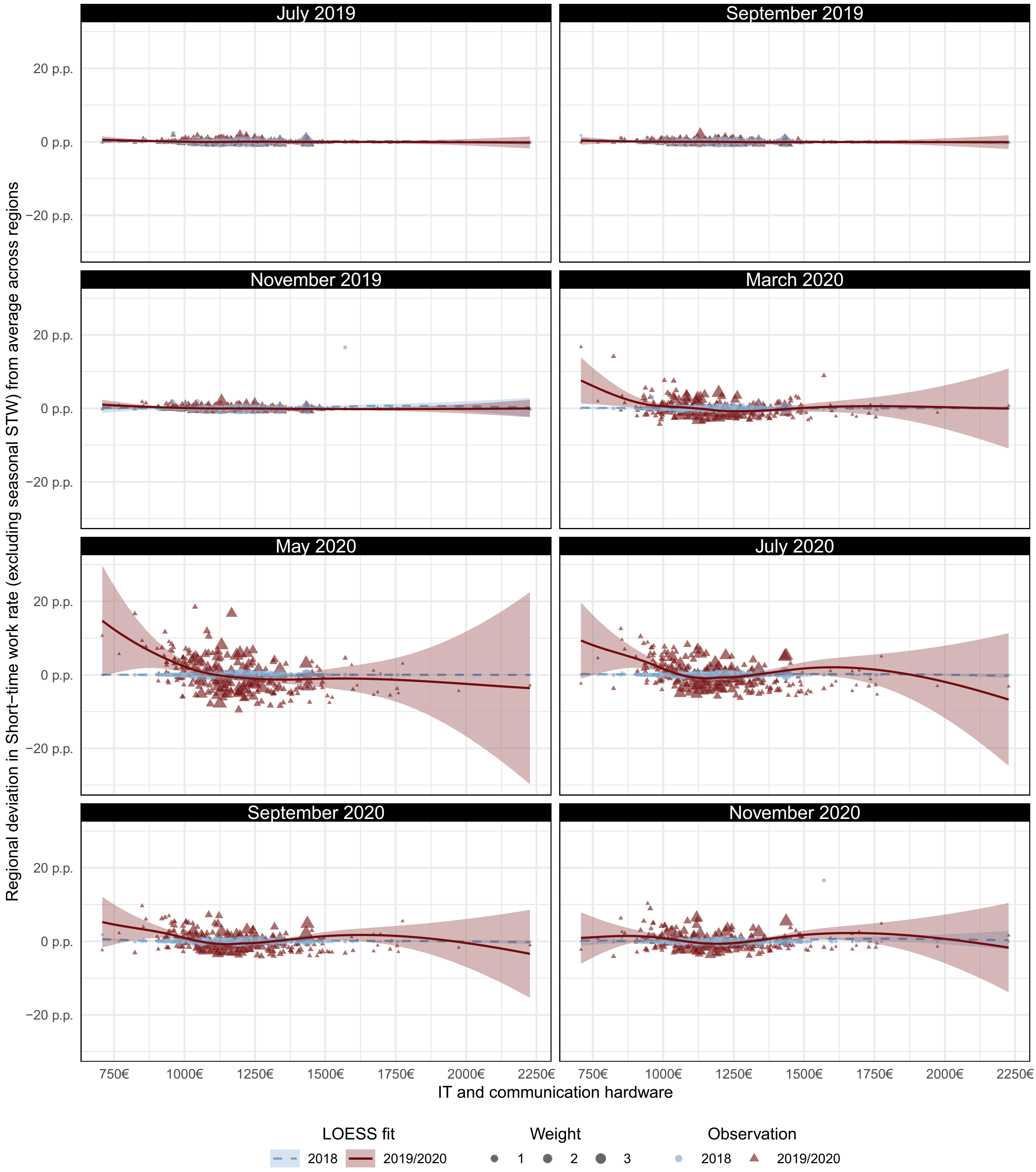

FIGURE B1 | Exposure-response-plots of digital capital and short-time work rates. *Note:* The figure reports deviation in short-time work rates for each 257 labour market regions with respect to the average over all regions. Short-time work rates are calculated as the number of workers using short-time work in a given month over the employment level in June 2019. Regions are ranked by their precrisis exposure to digital capital. The npCBPS weight of observations is represented by the size of dots/triangles.

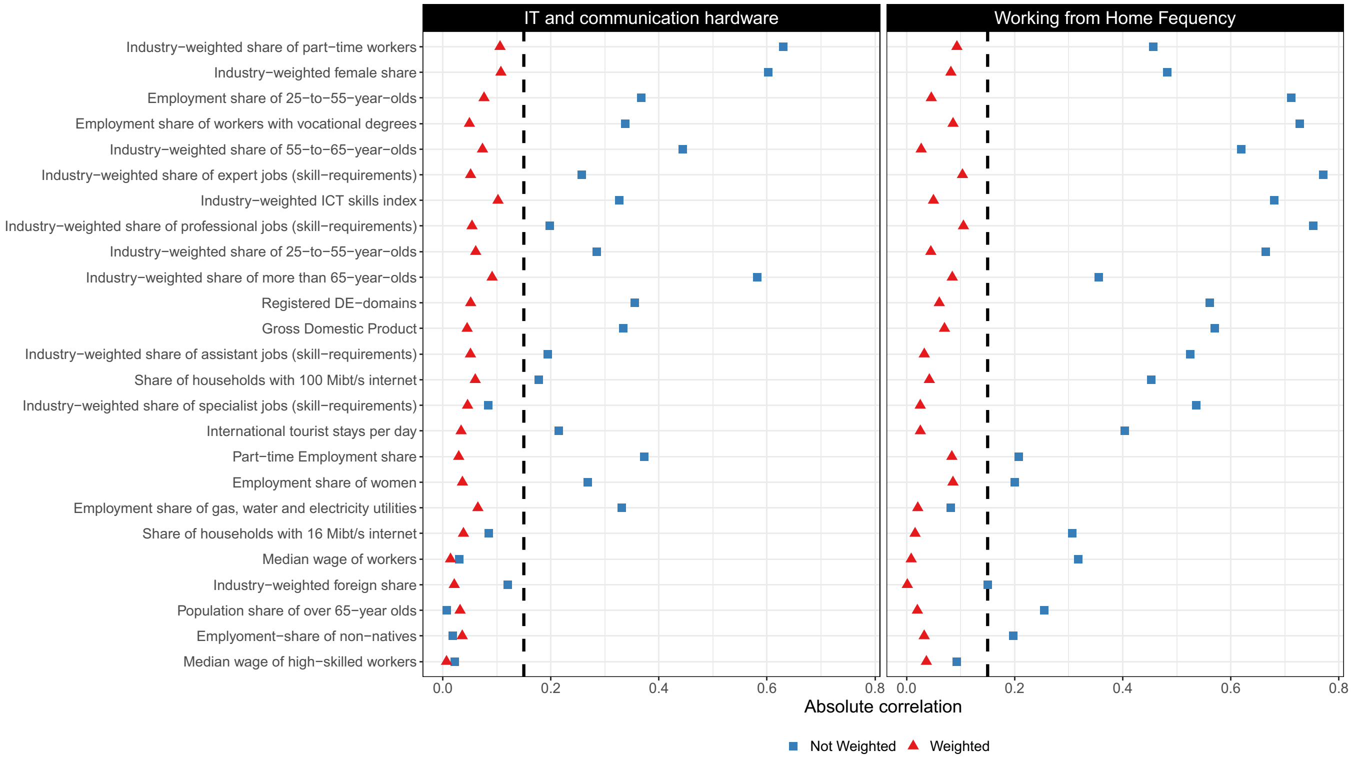

FIGURE B2 | Balance for nontargeted covariates. *Note:* The figure shows the absolute correlations between both trageted and nontargeted covariates in our npCBPS weighting procedure and the measure for exposure to digital capital both in the unweighted (blue squares) and the weighted sample (red triangles) for both Digital Capital and the Working from Home Frequency.

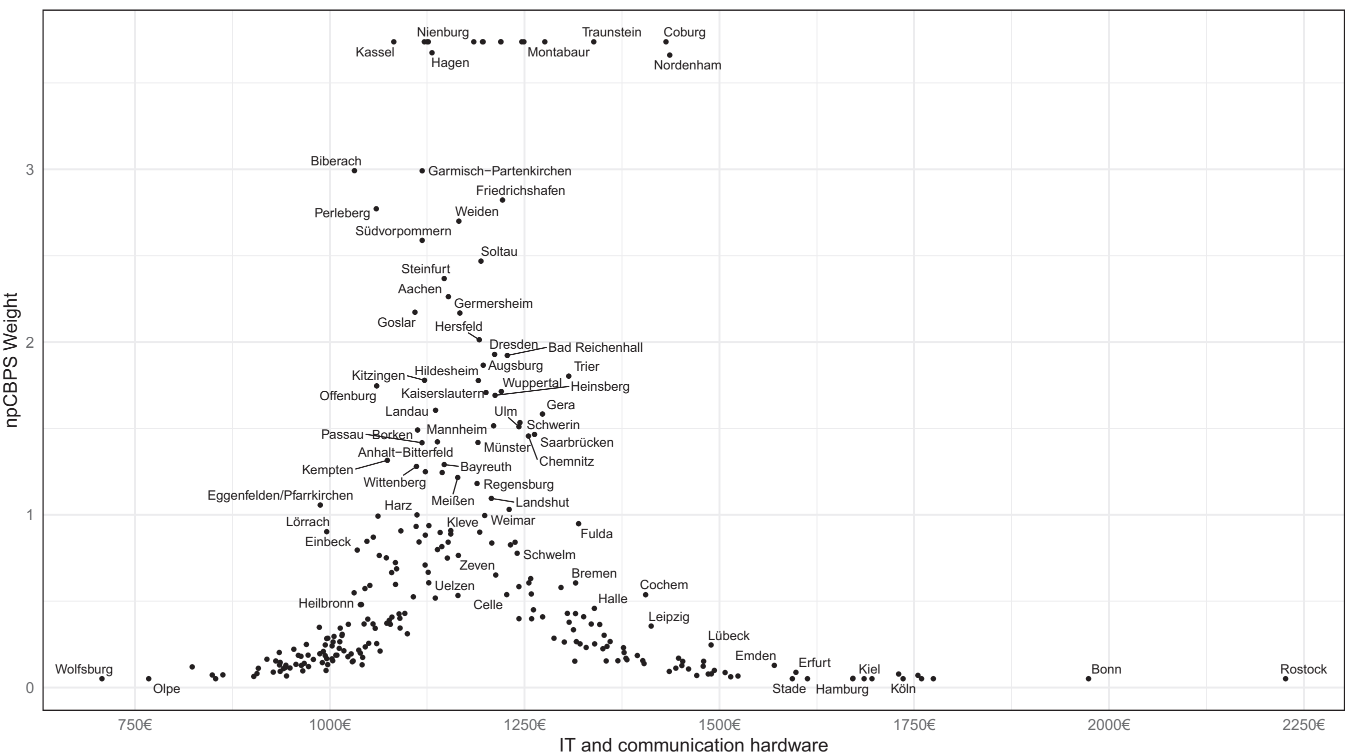

FIGURE B3 | Weight distribution for regressions with local digital capital. *Note:* The figure presents the npCBPS weights of regions along their digital capital distribution.

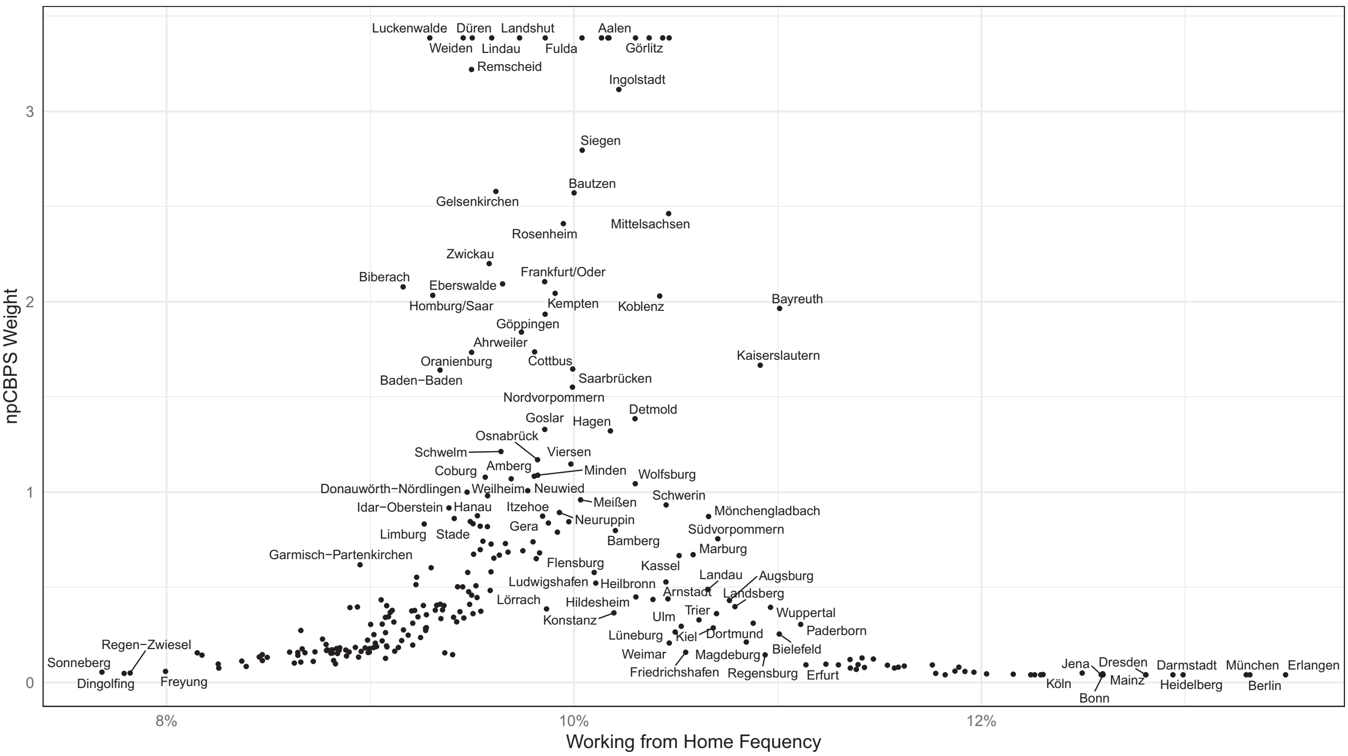

FIGURE B4 | Weight distribution for regressions with the Working from Home Potential. *Note:* The figure presents the npCBPS weights of regions along the regional working- from-home potential distribution.

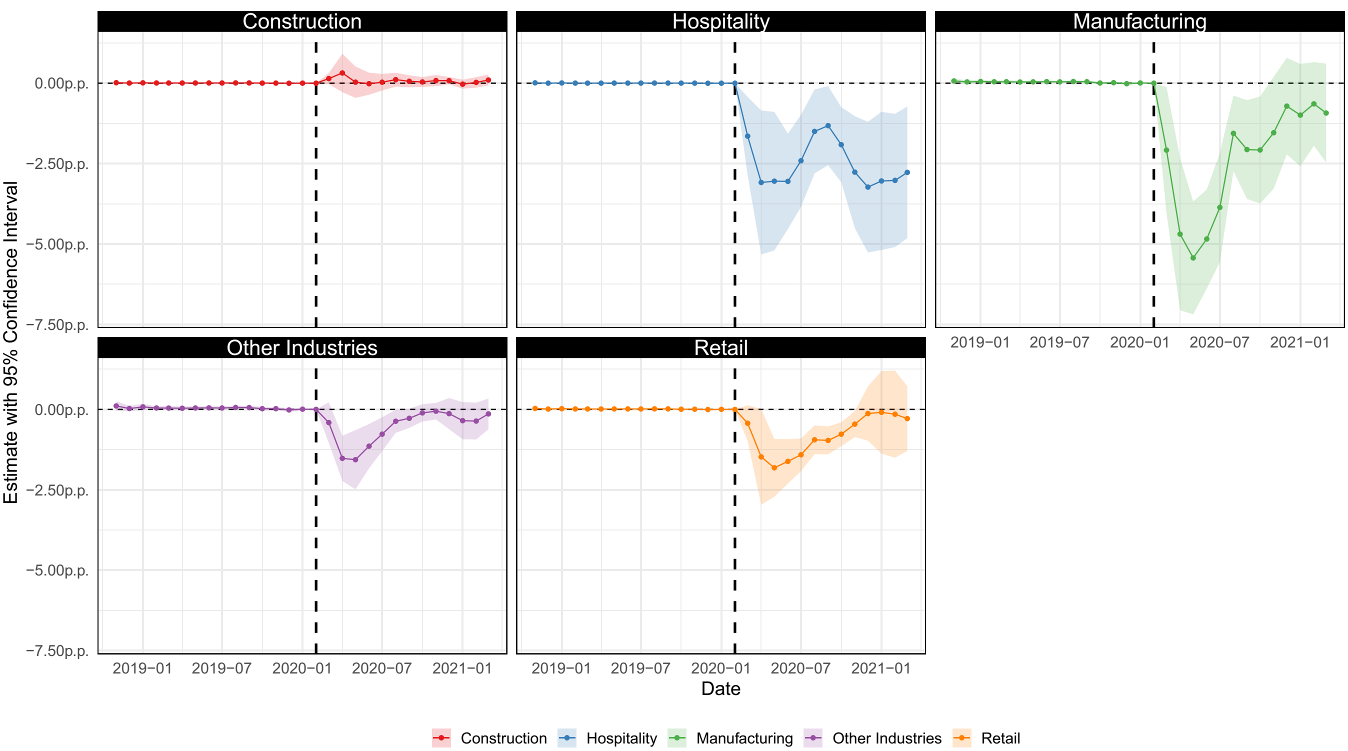

FIGURE C1 | Effect of digital capital on short-time work within broad industries. *Note:* The figure shows estimated changes in the incidence of short-time work (STW) across broad industry groups in response to a one standard deviation increase in local digital capital potential, relative to February 2020. STW incidence is defined as the monthly number of workers on STW in a given industry divided by industry-specific employment as of June 2019. For months before February 2020, industry-level STW rates are imputed by weighting total STW take-up by each region's employment shares across industries. Estimates are shown with 95% confidence intervals. Standard errors are clustered at the local labour market level.

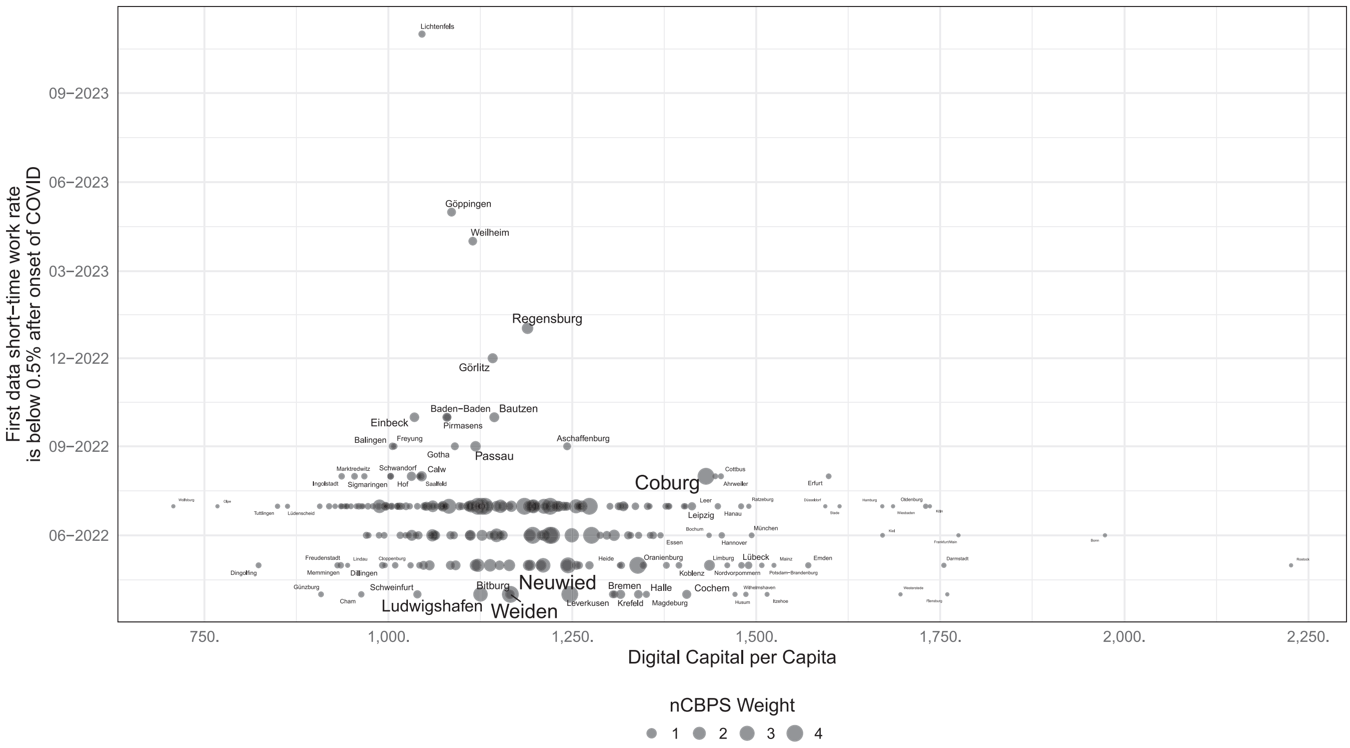

FIGURE C2 | Digital capital and recovery time. *Note:* This figure plots the relationship between digital capital per capita and the time to recovery, defined as the first date at which the short-time work rate fell below 0.5% after the COVID-19 shock. The marker size represents nCBPS weights used in the analysis.

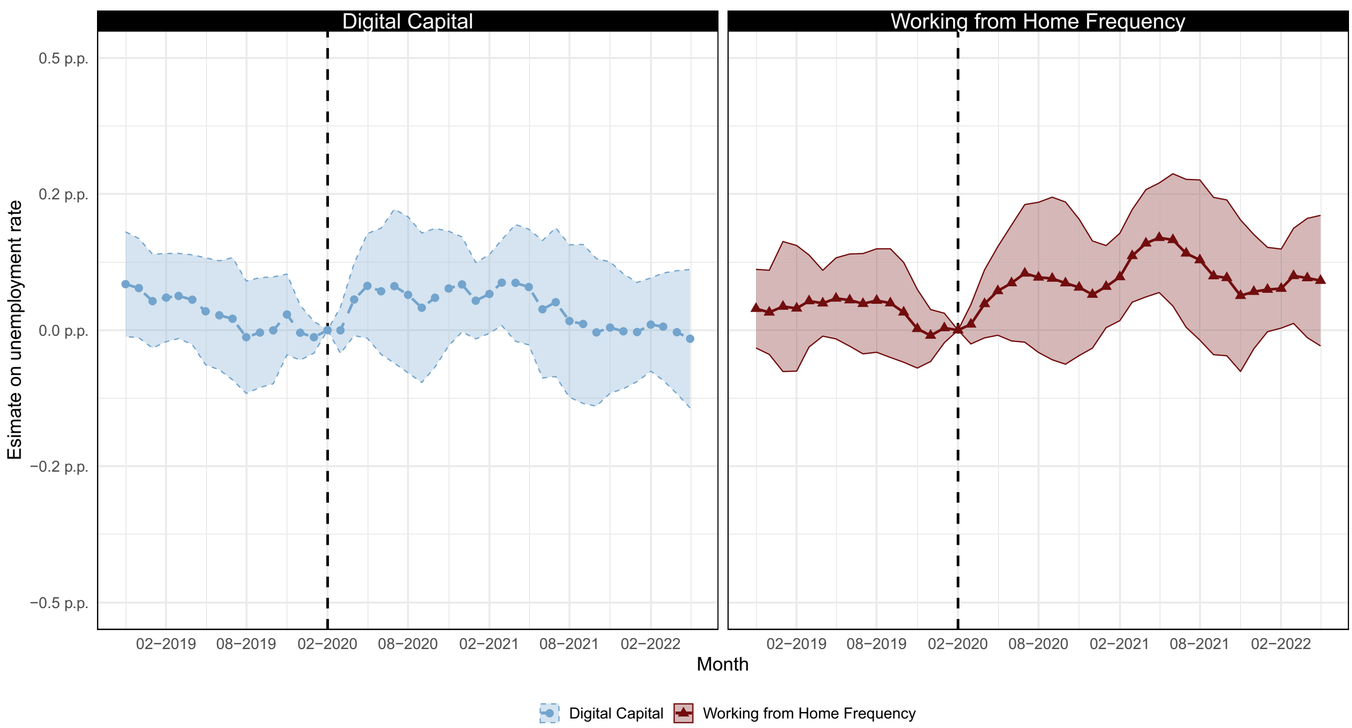

FIGURE C3 | Event study estimates on unemployment rates. *Note:* The figure reports the change in unemployment rates for a standard deviation increase in ICT capital (left panel) or working from home potential (right panel). Unemployment rates are calculated as the number of unemployed individuals in a given month over the employment level in June 2019. The npCBPS weight of observations is represented by the size of dots/triangles. Standard errors are clustered at the local labour market level.

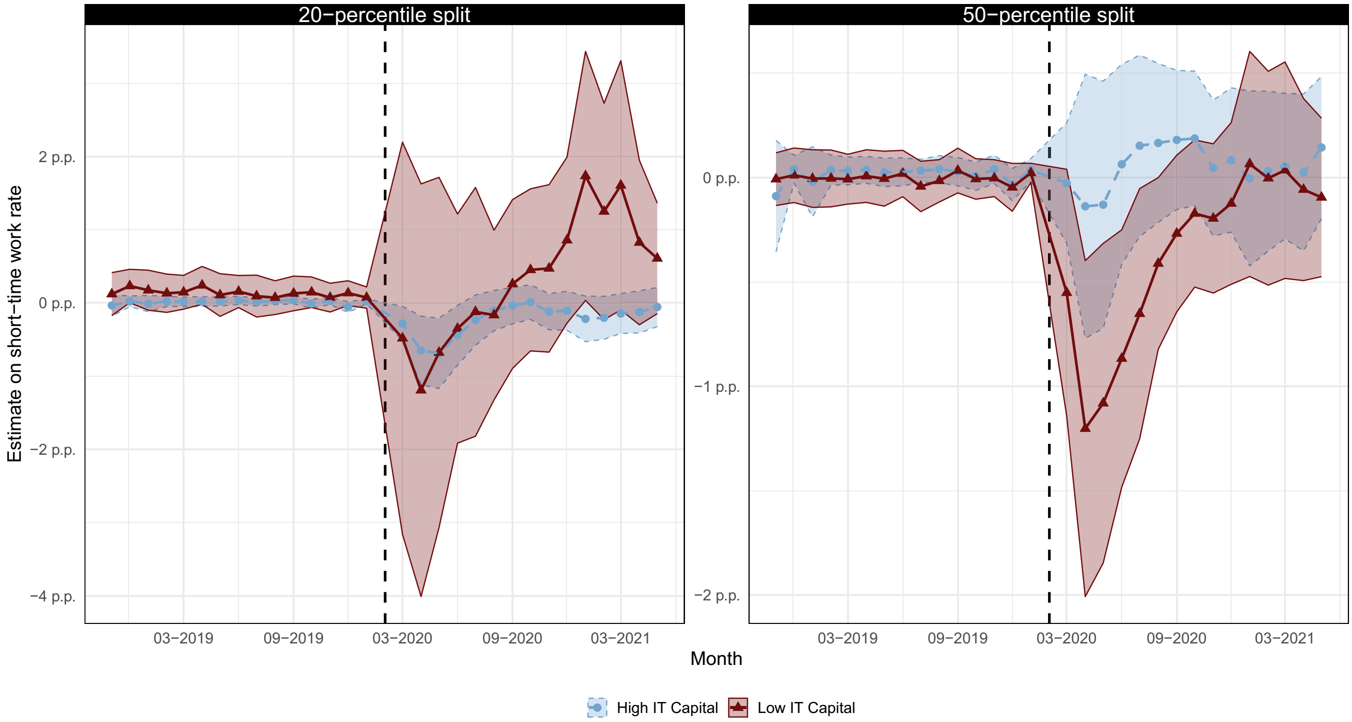

FIGURE C4 | Event-study estimates for working from home potential by high or low digital capital. *Note:* The figure reports the change in short-time work rates relative to February 2020 for a standard deviation increase in working from home potential. In blue are shown regions with high digital capital potential (highest 80% of regions in the left panel and highest 50% in the right panel), while in red are shown regions with low digital capital potential (lowest 20% of regions in the left panel and lowest 50% in the right panel). 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. Standard errors are clustered at the local labour market level.

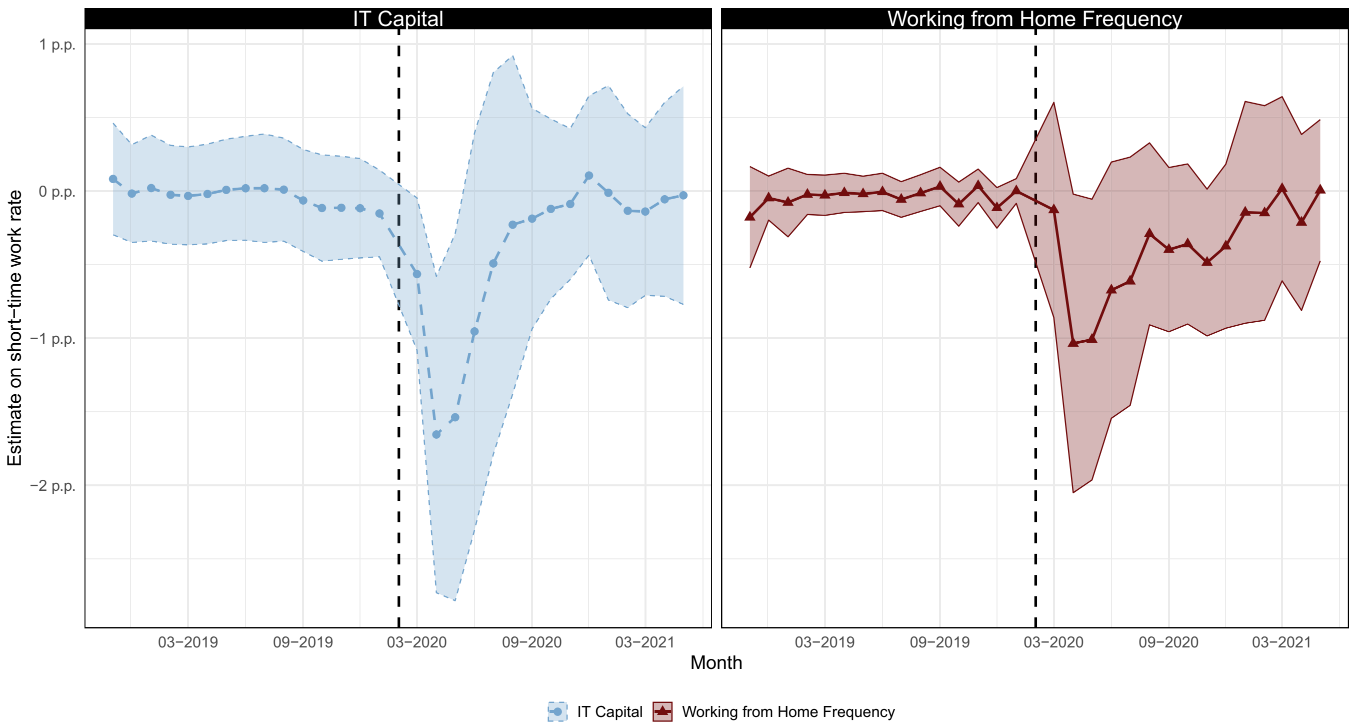

FIGURE C5 | Including digital capital and working from home potential in the same specification. *Note:* The estimates measure the change in short-time work rates relative to February 2020 for a standard deviation increase in digital capital potential (left panel) or in working from home potential (right 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. Standard errors are clustered at the local labour market level.