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Digitalization during the COVID-19 Crisis

Implications for Productivity and Labor Markets in Advanced Economies

Prepared by Florence Jaumotte, Longji Li, Andrea Medici, Myrto Oikonomou, Carlo Pizzinelli, Ippei Shibata, Jiaming Soh, and Marina M. Tavares

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Authorized for distribution by Pierre-Olivier Gourinchas
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ABSTRACT:
Digitalization induced by the pandemic was seen both as a possible silver lining to the crisis that could increase longer-term productivity and a risk for further labor market inequality between digital and non-digital workers. This note shows that the pandemic accelerated digitalization and triggered a partial catch-up by less digitalized entities in advanced economies. Higher digitalization levels substantially shielded productivity and hours worked during the crisis. However, the extent to which pandemic-induced digitalization led to structural change in the economy is less clear. Less digitalized sectors have rebounded more strongly, albeit after stronger declines, and while workers in digital occupations were more shielded from the crisis, there does not appear to be a structural change in the composition of labor demand. Meanwhile, shifts in labor supply are more likely to be permanent, driven by the increase in working from home.

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Author's E-Mail Address:	FJaumotte@imf.org; LLi4@imf.org; AMedici@imf.org; MOikonomou@imf.org; CPizzinelli@imf.org; IShibata@ifmf.org; JSoh@imf.org; MMendestavares@imf.org.

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Executive Summary

At the onset of the COVID-19 pandemic, policymakers and academics alike expected that the pandemic and subsequent containment policies would accelerate digitalization, speeding up structural change toward a more digital economy. This acceleration in digitalization was seen as a potential silver lining to the pandemic, equipping businesses with digital technologies that could increase productivity and growth over the long term. At the same time, there were concerns that digitalization could displace medium- and low-skilled workers, driving greater inequality in the labor market. Two years after the onset of the pandemic, productivity in many sectors remains below its precrisis trend, and labor markets are characterized by shortages of low-skilled rather than high-skilled workers. How much digitalization did actually take place? How did it affect productivity and labor markets during the pandemic? And what longer-term effects can be expected? This Staff Discussion Note sheds light on these questions for a selected group of advanced economies. With only two years of data available, proper caution should however be applied in interpreting the permanence of the results.

The COVID-19 pandemic did accelerate digitalization, measured as the share of workers using a computer with access to the internet in advanced economies, and while the increase was broad-based, the largest progress was observed in countries, sectors, and firms that started with low digitalization levels, including southern and eastern European countries, the food and accommodation sector, and smaller firms.

Digitalization helped substantially shield productivity and employment from the pandemic shock. At the height of the pandemic, controlling for the characteristics of the sector, labor productivity and hours' losses in highly digitalized sectors were significantly smaller relative to the same less digitalized sectors in other countries. Higher digitalization mitigated the economic disruptions from the pandemic, increasing aggregate productivity growth by a quarter and reducing the loss in hours worked by a third. In 2021, however, productivity and hours rebounded more strongly in less digitalized sectors that had experienced larger losses in 2020. While it is still early to appraise the longer-term effects of the recent digitalization induced by COVID-19, evidence for larger (publicly listed) firms shows a growing total factor productivity (TFP) differential between high- and low-digitalized firms at the exit of the crisis. Whether smaller firms will be able to reap the benefits from their investments in digitalization may depend on policies in place to ensure healthy competition in digital markets.

In labor markets, while workers in digital occupations were more shielded from layoffs than those in non-digital occupations during the crisis, there is little evidence so far of a structural shift in the composition of labor demand toward digital occupations. Vacancies data show that the initial increase in the share of digital occupations subsequently reversed, consistent with the high labor market tightness observed for lower-skilled workers. This suggests that the increase in digitalization was concentrated in primary digitalization forms that allowed businesses to perform activities without in-person interactions rather than fundamentally overhaul production. A more persistent change is the switch to work from home, which increases workers' welfare by reducing commuting time and improving time management flexibility, and could boost labor supply.

The pandemic has shown that digitalization may be important not only for longer-term productivity but also for the resilience of the economy to shocks. Digitalization can also enhance labor force participation by improving workers' work-life balance. Yet, while the pandemic has triggered some catch-up in digitalization, there remain substantial gaps in digitalization at the sectoral level across countries. To close these gaps and ensure gains are broadly shared, policies should focus on investing in digital infrastructure, helping workers acquire the needed skills, maintaining competition in digital markets, and adapting labor laws and regulations to telework.

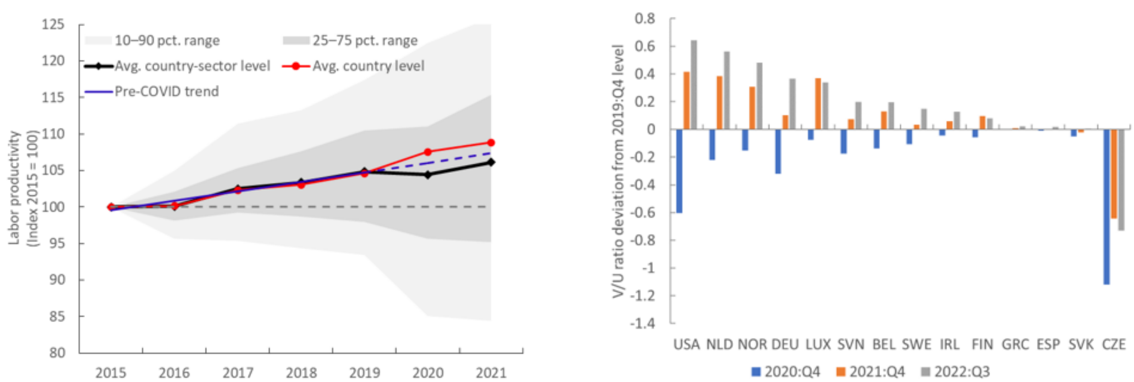
I. Introduction

At the onset of the COVID-19 pandemic, policymakers and academics alike expected that the pandemic and subsequent containment policies would accelerate digitalization, with potentially important implications for labor markets and productivity. Many workers had to switch from working in the office to working from home, and economic activities that are contact-intensive were restricted. As a result, many firms had to adjust to remote work and expand their activities online, which required changes in operations, logistics, and possibly a rapid investment in information and communication technology (ICT). During the COVID-19 pandemic, these forms of digitalization that allowed businesses to operate remotely may have supported employment and labor productivity, and there were also hopes that they would boost firms' and workers' productivity in the longer term. In contrast, expectations regarding long-term impacts on the labor market were more mixed, with fears that digitalization could displace swaths of low- and middle-skilled workers.

Figure 1. Labor Productivity and Labor Market Tightness

1. Trends in Labor Productivity across Countries and Sectors
(2015 = 100)

2. Labor Market Tightness (V/U)
(Deviation from 2019:Q4)



Sources: Eurostat; UK Office of National Statistics; US Bureau of Economic Analysis and Bureau of Labor Statistics; and IMF staff calculations.
Note: Panel 1: The black line and shaded areas show the unweighted average and percentile ranges across country-sector data. The blue line reports the pre-COVID trend for the average. The red line reports the unweighted cross-country average for country-level aggregate productivity. Labor productivity is defined as real value added per hour worked. Panel 2 shows the V/U ratio by country, where job vacancies (V) and unemployment (U) are seasonally adjusted. Data labels use International Organization for Standardization (ISO) country codes.

Two years after the pandemic, two emerging puzzles have challenged some of the priors, raising the question of how much digitalization picked up and how it impacted firms and labor markets. On the one hand, on average in advanced economies aggregate labor productivity rose following a common countercyclical pattern in recessions. Still, for many sectors, labor productivity experienced a substantial decline and has yet to realign with pre–COVID-19 trends (Figure 1, panel 1). This stands in contrast with expectations of an acceleration in productivity in the wake of pandemic-related IT investments. On the other hand, advanced economies' labor markets have tightened more, not less, for low-skilled jobs than for higher-skilled ones, as shown in a recent IMF Staff Discussion Note (SDN) titled "Labor Market Tightness in Advanced Economies" (Duval and others 2022) (Figure 1, panel 2).

Against this backdrop, this SDN sheds light on how much and how persistently digitalization picked up across advanced economies during the COVID-19 crisis and draws implications for productivity, employment, and inequality. The note (1) documents the dispersion of digitalization across countries, sectors, and firms before the COVID-19 crisis; (2) examines how the pandemic has impacted digitalization across countries, sectors, and firms; (3) investigates whether individual firms' and aggregate productivity increased in the process; (4) explores how firms’ responses have impacted hours worked and the demand for workers with different skills; (5) examines the implications of working from home for workers’ labor supply; and (6) discusses policy recommendations. Results should be seen as still preliminary and proper caution applied to their interpretration, given that only two full years of data were available at the time of the analysis.

Before the COVID-19 crisis, there were substantial differences in digitalization across countries, sectors, and firms, pointing to digitalization as a potentially key factor to explain differences in performance across countries. While in Sweden, the most digitalized country in the sample, 82 percent of workers used a computer with internet access in 2019, in Greece, the least digitalized country in the sample, only 38 percent of workers did so. These country differences were not driven by differences in sectoral composition alone: in the food and accommodation sector, for example, the difference in digitalization between Greece and Sweden was 38 percentage points. Across sectors and firms, contact-intensive industries historically had the lowest levels of digitalization, and small businesses were substantially less digitalized than medium and large firms—a result that holds broadly across countries.

The COVID-19 crisis triggered an increase in digitalization, particularly in countries, sectors, and firms that started the crisis with low digitalization levels. The data point to an acceleration in digitalization during the pandemic, relative to precrisis trends. For the sample, over the course of two years, the share of workers using a computer with internet access increased from 56 to 61 percent on average, about a 10 percent increase. Greece, the country with the ex-ante lowest level of digitalization, experienced the second most significant increase, of almost 20 percent. Looking across sectors and firms, the same pattern of greater investment in less digitalized entities arises.

Digitalization helped shield productivity substantially during the pandemic. The empirical analysis shows that at the height of the pandemic, in 2020, higher digitalization in a sector reduced labor productivity losses by 20 percent when comparing the 75th and 25th percentiles of digitalization. If countries with low digitalization had had in each sector the 75th percentile of digitalization observed in the sample for that sector, aggregate labor productivity growth during the pandemic would have been higher by a quarter. In 2021, sector-level labor productivity experienced a partial rebound, and that rebound was larger in less digitalized sectors, which had experienced larger declines in the previous year.

While it is still early to observe the longer-term effects from these investments in digitalization, historical evidence suggests it could boost productivity growth. Evidence from publicly listed firms in the US and advanced European economies shows that highly digitalized firms’ TFP recovered more strongly from the pandemic than that of low-digitalized firms. The stronger results for TFP growth could, however, also reflect that these were obtained for larger firms that may be in a better position to leverage their investments in digitalization due to economies of scale and network effects.

Digitalization also played an important role in the protection of hours worked during the COVID-19 crisis. The empirical analysis suggests that at the sectoral level, greater digitalization translated into smaller losses in hours worked, especially in non-contact-intensive sectors, reducing these by 85 percent between the 75th and 25th percentiles of digitalization. At the country level, if less digitalized countries had had a digitalization level equivalent to the 75th percentile of each sector, employment losses from the pandemic-induced disruptions would have been a third lower in 2020. Digitalization thus helped sustain both employment and labor productivity during the crisis.

Workers in digital occupations were better shielded from the impact of the COVID-19 crisis; however, there is no sign of a permanent increase in the demand for digital workers. The empirical analysis shows that workers employed in digital occupations were less affected by layoffs relative to workers in non-digital occupations, particularly in countries without job retention programs. This effect was broad-based across digital occupations. A possible reason for the apparent lack of structural labor market impact is that the increase in digitalization observed is concentrated in primary digitalization forms that allow businesses to perform activities without in-person interactions rather than fundamentally overhaul production via advanced digital technologies.

One more persistent transformation is the working-from-home revolution, which could boost labor supply. The increase in working from home is so far a more persistent trend that has changed the labor market, increasing the welfare of workers employed in teleworkable occupations. Before the crisis, this arrangement was rare; on average, only 5 percent of workers typically worked from home in Europe. By 2021, the share of workers who usually work from home increased to more than 16 percent. Working more often from home can generate significant welfare gains associated with reducing commuting hours and greater time management flexibility. By reducing the disutility of work, working-from-home arrangements could help increase attachment to the labor market and boost labor supply.

On the policy front, governments should find the right balance between supporting further productive digitalization by firms and continuing equipping workers to adapt to a more digital world. The analysis points to potential benefits of digitalization not only for long-term growth but also for the capacity to withstand shocks, increasing economic resilience. A more digital economy can also encourage more extensive labor force participation by giving workers flexibility regarding their work arrangements. There remain large differences in digitalization across countries despite the pandemic-induced digitalization push, in part reflecting differences in the cost of digital services and the availability of science, technology, engineering, and mathematics (STEM) skills in the population. Governments can help close these gaps by investing in digital infrastructure and helping workers acquire the needed skills. They should also ensure that gains are broadly shared by maintaining healthy competition in digital markets and adapting labor laws and regulations to changing work environments to facilitate telework or remote work access.

II. Stylized Facts

The primary measure of digitalization used in the analysis is the share of workers using a computer with access to the internet. This measure, available from Eurostat, is chosen because of its broad coverage across countries, sectors, and time. In addition, this measure can capture some digitalization needs brought about by the pandemic, like the increase in online sales and contactless payments. However, this measure cannot capture changes in technology use or the introduction of more advanced technologies. Box 1 discusses data on more advanced technologies, such as artificial intelligence (AI), cloud computing, and big data. Except for cloud computing, these measures tend to have a low penetration level in most sectors, fewer differences across countries and sectors (likely reflecting their more specialized character), and a much less dynamic behavior over the COVID-19 period.[1] For the US—for which the Eurostat measure is not available, digitalization is measured by software spending per employee, available at the sectoral level, and computer and software assets per employee, available at the firm level for publicly listed firms. The analysis is focused on advanced economies for which these digitalization measures are available.[2]

Before the COVID-19 crisis, there were significant differences in digitalization across countries, sectors, and firms. The share of workers who used a computer with internet access was close to 80 percent in Denmark and Sweden, but less than 40 percent in Greece and Portugal (Figure 2, panel 2). Across sectors, contact-intensive sectors, like food and accommodation, had fewer than 40 percent of workers using a computer with access to the internet, while over 90 percent of workers were digitalized in the ICT and the professional, scientific, and technical services sectors (Figure 2, panel 4). Across firms, small firms were also less digitalized than medium and large firms. However, differences across firms' sizes are much smaller than those across countries (Figure 2, panel 3). Differences in digitalization across countries were mostly attributable to digitalization gaps within sectors, rather than differences in countries' sectoral compositions, and they were related to the cost of internet broadband.[3] There were large differences across countries in the latter, with, for example, the cost of fixed-broadband internet in Greece and Portugal almost two times that of Norway.

The COVID-19 crisis accelerated digitalization in advanced European economies and prompted a catch-up of countries, sectors, and firms that started from lower levels of digitalization (Figure 2, panel 1). On average, digitalization increased above trend during the pandemic from 56 percent of workers using a computer with internet access to 62 percent, a 6 percentage point rise (10 percent in proportional terms). This acceleration in digitalization was observed in most advanced economies (Figure 2, panel 2) and in most sectors (Figure 2, panel 3). Countries that started with a low level of digitalization tended to experience larger increases in digitalization during the pandemic. For instance, Greece saw an increase in digitalization of almost 20 percent above trend, in contrast with highly digitalized economies, such as Denmark, France, Germany, and The Netherlands, which experienced a slight decline in digitalization relative to trend. A sectoral decomposition reveals that countries' increases in digitalization were driven primarily by improvements within sectors rather than sectoral reallocation.[4] In Portugal and Slovenia, which are the countries where sectoral reallocation was more relevant, reallocation contributed only about 20 percent of the increase in digitalization. The same catch-up dynamics were also at work at the firm and sector levels, with small firms and contact-intensive sectors like food and accommodation and construction experiencing the largest increases.

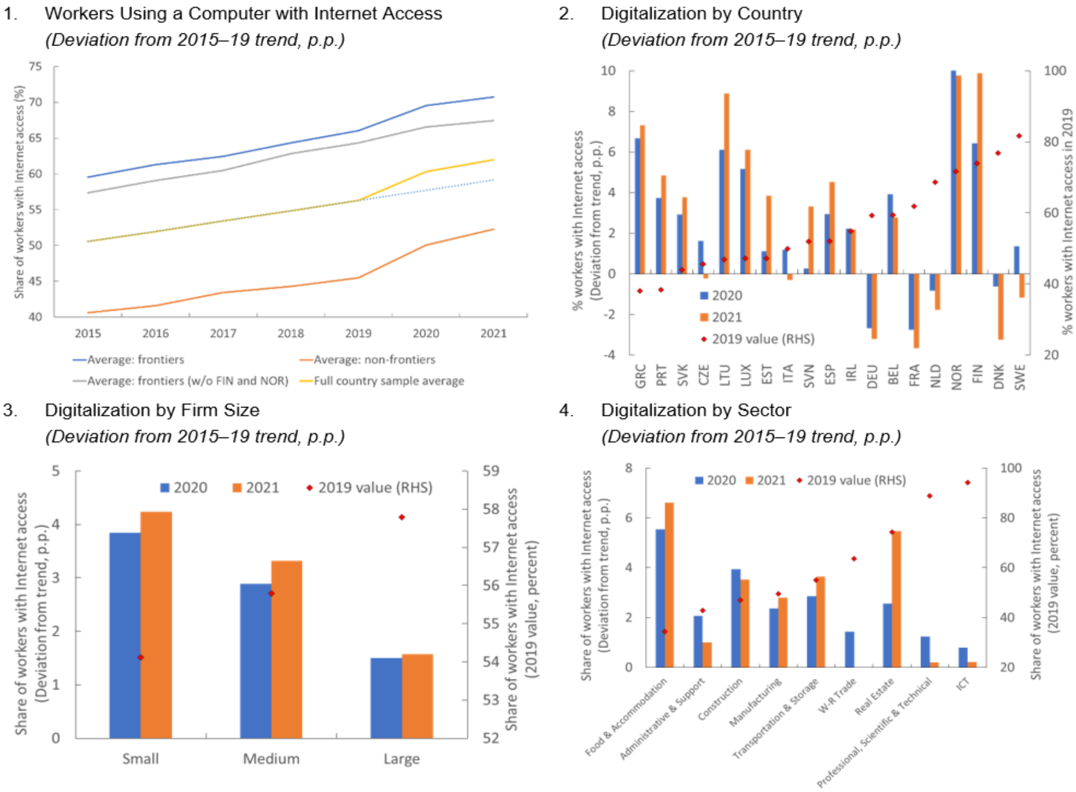
[1] Advanced technologies hold the greatest potential to deliver productivity growth and labor markets disruptions compared with standard computer infrastructure. However, their implementation requires more planning and larger investments. Hence, digitalization based on advanced technologies is less likely to respond to short-term disruptions caused by the pandemic, particularly in low-digitalization sectors where they are less directly applicable.

[2] Dabla-Norris and others (2023) present a deep analysis of digitalization in the Asia and Pacific region, reaching similar conclusions. Amaglobeli and others (forthcoming) document digitalization trends in Emerging Market and Developing Economies.

[3] Annex 2 describes the cross-country decomposition analysis.

[4] Annex 2 describes the sectoral decomposition analysis.

Figure 2. COVID-19 Has Accelerated Digitalization in Advanced European Economies



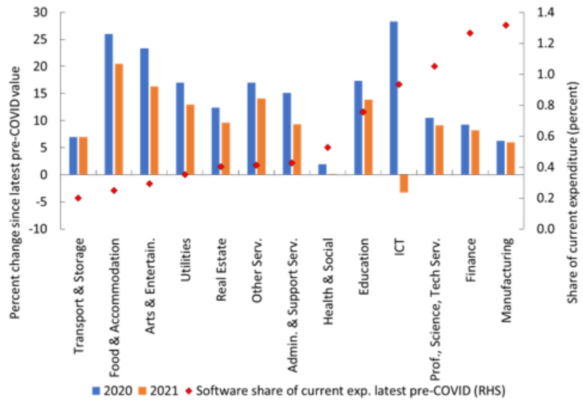
Sources: Eurostat; International Telecommunication Union; and IMF staff calculations.
Note: Digitalization is measured using the share of workers with access to a computer with Internet access. Panels 1,3, and 4 show unweighted averages across countries in the sample (BEL, CZE, DEU, DNK, ESP, EST, FIN, FRA, GRC, IRL, ITA, LTU, LUX, NLD, NOR, PRT, SVK, SVN, and SWE; LVA is not included due to missing 2015 data). Digitalization frontier countries are those having share of workers with Internet access greater than the sample median. Measure is not available for the United States. ICT = information communication technology; W-R = wholesale and retail. Data labels use International Organization for Standardization (ISO) country codes.

Data for the US also show an increase in digitalization during the COVID-19 pandemic, particularly in contact-intensive sectors that have a more significant share of small firms. Using spending for software services per employee as a proxy for digital intensity, all industries spent more on digitalization in 2020 than they did in the latest year of available data before COVID-19 (Figure 3, panel 1). While in absolute terms the rise in spending was higher in sectors with higher digital intensity prior to the pandemic, in relative terms some of the largest rises took place in sectors with historically lower levels of digitalization. Some of these are contact-intensive sectors that were the most adversely affected by the pandemic, such as the arts and entertainment and the food and accommodation sectors. Furthermore, similarly to other advanced economies, these sectors feature a greater share of small firms relative to the rest of the economy (Figure 3, panel 2). Part of the increase in digital spending reversed in 2021, but the overall level of spending remained higher than pre-COVID levels, except in the ICT and the health and social sectors.[5] Data for publicly listed US firms (not shown here) suggest that in 2020, COVID-19 incentivized less digitalized US firms to invest relatively more in computers and software per worker, but in 2021 this pattern reversed, with more digitalized firms investing relatively more in the case of the US.

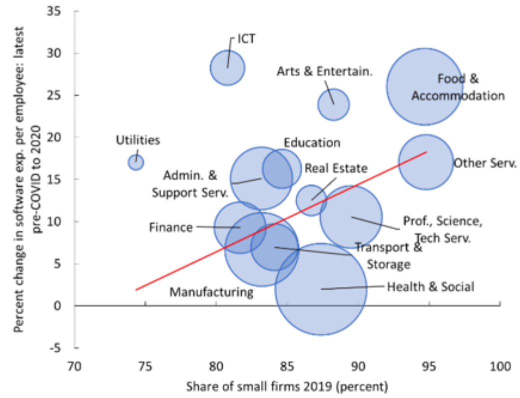
[5] Annex Figure 1.1 shows that results hold when using the share of software spending in total current expenditures.

Figure 3. Digital Intensity Increased in the US

1. US: Software Spending per Employee by Sector
(Percent change relative pre-COVID level)



2. US: Share of Small Firms and Growth in Software Spending by Sector
(2016–20)



Sources: US Census Bureau Annual Survey of Manufactures and Service Annual Survey; and IMF staff calculations.
Note: In panels 1 and 2, the latest available pre-COVID year is 2019 for manufacturing and 2017 for all other sectors. The percentage changes from the pre-COVID period to 2020 are turned into annual rates for comparability. In panel 1, the variable on the RHS y-axis is the percent change in software spending per employee while the variable on the LHS y-axis is the share of software expenditure as a share of total current expenditure in the sector. In panel 2, the y-axis also reports the percent change in software spending per employee, while the x-axis reports the share of firms with 10 to 100 employees, which are considered “small” firms. The share is computed based on firms with 10 or more employees, thus excluding “micro” firms. The marker sizes represent the employment share in 2019. The red line reports the best fit from a linear regression with sectors weighted by the employment level in 2019. All expenditures are deflated to 2019 prices.

III. Productivity

There are multiple channels through which digitalization may have increased productivity. First, the pandemic has forced many firms to purchase equipment and software platforms (like Zoom and Microsoft Teams) to allow workers to work from home and facilitate meetings and scheduling. These investments can increase workers’ productivity by saving commuting time, reducing attrition, facilitating interaction, and enhancing job satisfaction (Bloom, Han, and Liang 2022). In contrast, the disruption of traditional work modes and the demands of child and family care during the pandemic may have reduced the productivity of working from home with digital technologies compared with in-office work. Third, the pandemic has pushed many firms to invest in digital platforms to improve logistics and online sales. The access to digital technologies can increase productivity by extending market reach and operations. Historically, investments in IT are associated with higher levels of productivity. Brynjolfsson and Yang (1996), Brynjolfsson and Hitt (2000), Oliner and Sichel, (2000), and Crépon and Heckel (2002) review the literature on ’80s, ’90s, and 2000s IT adoption using growth accounting methodology and find that IT had a positive impact on productivity and growth.

To investigate the impact of the COVID-19 digitalization push on productivity, this note uses two measures of productivity. One is labor productivity, measured as output per hour worked. The advantage of this measure is that it covers the entire economy or activity in a sector; the drawback is that it can be impacted by changes in capital investment or skill composition of the labor force that occurred during the crisis.[6] To address this issue, the note also uses a second measure, total factor productivity at the firm level, which provides a cleaner measure of underlying productivity developments but is so far available only for a sample of publicly listed firms.

[6] Focusing on output per hour worked rather than output per worker also helps account for the diverse coverage of job retention programs across countries and sectors and their impact on employment.

III.1 Digitalization and Labor Productivity

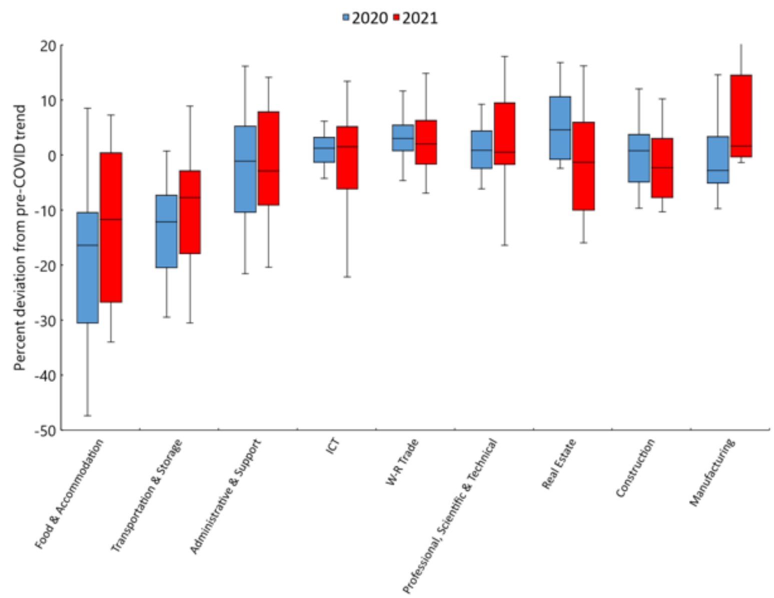
The analysis focuses on sectoral developments, which can provide insight into the effects of the changes in technology rather than in aggregate labor productivity. During crises, aggregate labor productivity increases because of labor shedding and reallocation toward more productive sectors in a common countercyclical pattern. The COVID-19 pandemic had a similar effect.[7] As a result, the increase in aggregate labor productivity during the pandemic (Figure 1, panel 1) cannot be attributed solely to digitalization. To better understand the impact of digitalization, this note uses a Google mobility indicator to capture the severity of the pandemic and lockdown measures across countries, as well as differences in levels of digitalization across sectors and countries. By examining differences in sectoral developments, it can better shed light on the effects of digitalization on productivity beyond its cyclical behavior.

The impact of COVID-19 on labor productivity was highly heterogeneous across sectors and countries (Figure 4)**.** Some industries were more severely hit by the pandemic, while others saw at least temporary increases in demand for their products (Alfaro, Becerra, and Eslava 2020; Barrot, Grassi, and Sauvagnat 2021). Ireland, for example, as a hub for start-ups and large companies in the ICT sector, particularly stands out for its labor productivity growth. Figure 4 suggests that industries with lower levels of digitalization in 2019, such as food and accommodation and transport and storage, generally suffered deeper productivity losses over 2020–21. However, there are also marked differences within each sector—particularly in food and accommodation, administrative and support services, real estate, construction, and ICT—indicating also strong heterogeneity across countries.

Figure 4. Covid-19 Has Impacted Negatively Labor Productivity

Cross-Country Distribution of Productivity Changes by Sectors

(Percent deviations from country-specific pre-COVID trends)



Sources: Eurostat; UK Office of National Statistics; US Bureau of Economic Analysis and Bureau of Labor Statistics; and IMF staff calculations.

Note: The figure shows the distribution of percent deviations from pre-COVID-19 trends within each sector. The horizontal line within the box represents the median, the box edges are the 25th and 75th percentiles, the whiskers report the upper and lower adjacent values. Country sample: AUT, BEL, CZE, DEU, DNK, ESP, EST, FIN, FRA, GBR, GRC, IRL, ITA, LTU, LUX, LVA, NLD, NOR PRT, SVK, SVN, SWE, USA. ICT = information communication technology; W-R = wholesale and retail.

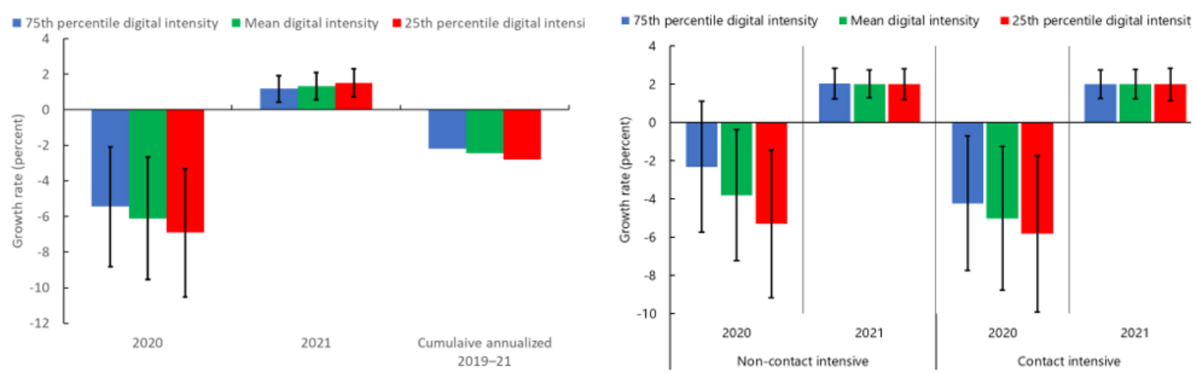
[7] This note focuses on measuring the impact of digitalization itself on productivity and does not attempt to provide a full account of the evolution of productivity during the crisis. Historically, recessions are associated with increases in underlying labor productivity and TFP due to "creative destruction," the reallocation of labor and capital toward more productive firms, and the decline in the opportunity costs of investment. Despite all these upsides, the pandemic has also generated an increase in uncertainty, drained firms' cash flows, and disrupted production processes and supply chains, which may lead to a decline in long-term productivity. Recent evidence based on the US suggests that the pandemic is having only a modest impact on TFP and labor productivity (Fernald and Li 2022).

Regression analysis shows that higher levels of digital intensity in a sector were associated with substantially reduced sectoral labor productivity losses at the height of the pandemic.[8] A regression is run on a panel of nine individual sectors in 22 advanced European economies over the period 2020–21, where the sector's yearly labor productivity growth rate is the dependent variable.[9] Although with large uncertainty around the point estimates, in 2020 the sectoral productivity loss in response to the pandemic shock was 20 percent smaller for a high level of digital intensity (75th percentile of the sector-adjusted distribution) than for a low level of digital intensity (25th percentile). In 2021, less digitalized sectors caught up somewhat, rebounding more strongly than those that were more digitalized, which had experienced smaller declines in 2020 (Figure 5, panel 1). However, as this catch-up was only partial, cumulatively over the two years of the pandemic, higher digitalization was associated with a modest buffering of the drop in productivity.

Figure 5. Regression Results on Labor Productivity

1. Predicted Productivity Growth by High and Low Digital Intensity

2. Productivity Growth by High and Low Digital Intensity and Contact Intensity



Sources: Eurostat; Organisation for Economic Cooperation and Development; and IMF staff calculations.
Note: Panel 1 plots a linear combination of the estimated regression coefficients representing the predicted labor productivity growth rate, in a country experiencing an average change in mobility, for a sector with high (75th percentile), average, or low (25th percentile) digital intensity based on a sector-adjusted distribution (i.e., abstracting from differences across sectors in the average level of digitalization). Panel 2 shows the derived labor productivity growth rates in three selected sectors for cases of high and low digital intensity based on the 75th and 25th percentiles of the specific distributions of digital intensity, separately for non-contact-intensive and contact-intensive sectors. The 90 percent confidence intervals in all bars test against the null hypothesis that the linear combination of coefficients is different from 0. A test for the difference between the low- and high-digitalization bars rejects the null hypothesis that these are equal for both 2020 and 2021. Country sample: AUT, BEL, CZE, DEU, DNK, ESP, EST, FIN, FRA, GBR, GRC, IRL, ITA, LTU, LUX, LVA, NLD, NOR, PRT, SVK, SVN, SWE. Annex 3 describes the regression specification and the data in detail.

An additional specification shows that the association between digitalization and productivity is more pronounced in non-contact-intensive sectors. The regression is augmented to allow the association between mobility and productivity to differ for contact-intensive and non-contact-intensive sectors. Figure 5, panel 2, shows that differences in productivity growth based on digital intensity are more marked for non-contact-intensive sectors, where the contraction for a highly digitalized sector (75th percentile) is 40 percent smaller than for one with low digitalization (25th percentile) in 2020. Two channels drive this result. First, the responsiveness of productivity to digitalization is higher for non-contact-intensive sectors. Second, these

[8] The benefits of digitalization adoption during the crisis was also documented in Copestake, Estefania-Flores, and Furceri (2022) using balance sheet data from 24,000 firms in 75 countries, and Oikonomou, Pierri, and Timmer (2023) using data on IT adoption covering almost three million establishments in the US.

[9] Annex 1 describes the construction of the COVID-19 shock, and Annex 3 describes the baseline regression specification and its extensions in detail. The explanatory variable of interest is a proxy for the intensity of the COVID-19 shock, both in its un-interacted form and interacted with the sector's share of workers using a computer with internet access. The variable used to reflect the COVID-19 shock is the year-over-year change in the Google mobility indicator at the country level. The set of other right-hand side variables includes controls for the countries' demographic characteristics, the coverage of job retention programs in 2020, sector fixed effects, the un-interacted digital intensity, and countries' fiscal support in 2020.

industries are characterized by a larger dispersion of digital intensity across countries. Nevertheless, even in contact-intensive sectors, a higher level of digitalization helped shield labor productivity in 2020. The presence of these differences within contact-intensive sectors as well thus suggests that digitalization holds explanatory power even when accounting for other sectoral characteristics.

Overall, differences in digitalization across countries within a given sector played a significant role for aggregate productivity dynamics. Differences in digitalization across countries within a given sector were large enough to produce substantial differences in labor productivity growth at the height of the pandemic. To quantify the effect on aggregate labor productivity, counterfactual country-level productivity series are constructed using the estimated regression coefficients and assuming that low-digitalization countries (those with a country-level digital intensity below median) had instead the average or 75th percentile level of digitalization observed in the sample for each sector. In such a scenario, sector-level labor productivity losses associated with the Google mobility shock would have been reduced. Consequently, once accounting for shifts in the share of each sector in total employment, the average growth rate of aggregate productivity in 2020 in these countries would have been higher by 0.6 percentage point—approximately a quarter of their effective growth rate.[10]

A further question that is still open is whether sectors that increased their digital intensity most in the wake of the pandemic will experience medium-term productivity benefits from such investments. Section II showed that the acceleration in digital intensity since 2019 originated from sectors with lower initial levels. Because these sectors also suffered the largest productivity losses and a stronger rebound, the short time span of 2020–21 does not make it possible to disentangle the short-term effects of exposure to the pandemic from the potential gains from the recent investments. The next section provides some evidence of the medium-term productivity gains from investment in digitalization using more granular firm-level data.

III.2 Digitalization and Firm Total Factor Productivity

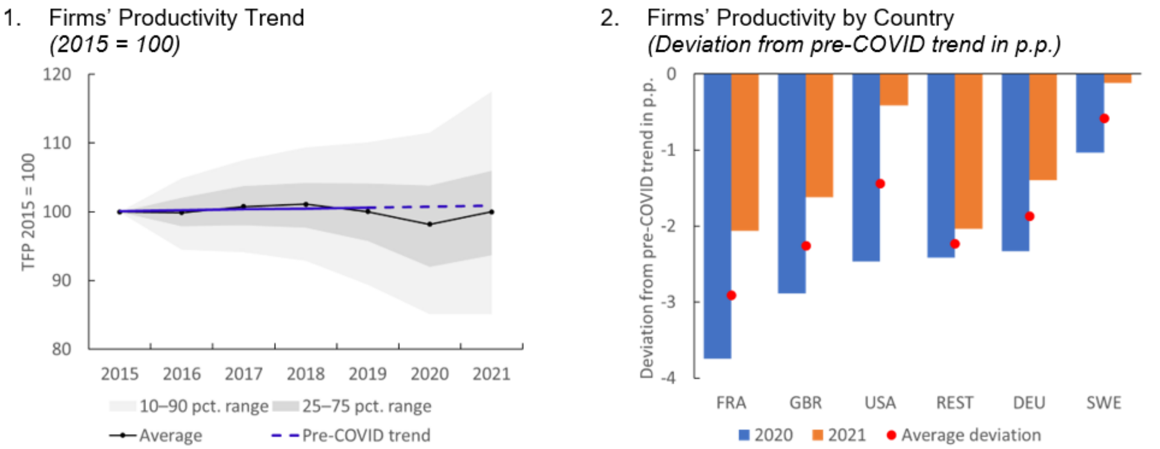
Data for publicly listed firms in the US and advanced European economies show that COVID-19 also led to a decline in TFP followed by a rebound. The pandemic accelerated a slowdown of TFP that started in 2018, lowering it by 1.8 percent in 2020 relative to 2019. However, in 2021 there was on average a reversal, with TFP growth catching up to and—in the case of the US—almost reaching the pre-pandemic level (Figure 6, panel 1). The recovery of TFP growth was more anemic in advanced European economies compared with the US.[11] This region is characterized by large cross-country heterogeneity in pre-pandemic digitalization (Figure 2, panel 1) and large differences in TFP growth recovery (as highlighted by Figure 6, panel 2). Next, the role of digitalization for TFP dynamics during the pandemic is analyzed. Unlike in Section III.1, which focuses on sectoral labor productivity and economy-wide dynamics, the focus of this section is on firms, and because of data availability the analysis is conducted on publicly listed firms only; that is, firms that tend to be larger and more digitalized.

[10] Annex 3 provides details of the counterfactual exercises. The counterfactual provides an illustrative quantification of the relationship between digitalization and productivity fluctuations. In practice, the thought experiment of moving in each sector the share of workers using an internet-connected computer to the 75th percentile of digital intensity would also likely require investments in broader IT infrastructure.

[11] Bloom and others (2020) study the impact of COVID-19 on firm-level TFP in the UK using accounting data from Bureau van Dijk's FAME data set and the Decision Maker Panel survey. They find that TFP fell by up to 5 percent during 2020–21.

Firms that were ex ante more digitalized left the crisis somewhat faster than less digitalized firms. Highly digitalized firms are defined as firms in the top 25 percent of the distribution of the share of computer and software assets per worker for the case of the US and by firms in country-sector cells in the top 25 percent of the distribution of the share of workers with internet access for advanced Europe. Employing a balanced panel of firms—and thus abstracting from entry-exit firm dynamics—both for the US and advanced Europe, by 2021, the gap between the TFP growth rate of more and less digitalized firms was growing (Figure 7, panels 1 and 2). However, part of the differences across high- and low-digital firms could be explained by gaps in digitalization across sectors. Further regression analysis is conducted to explore differences in low- vs high-digital firms, controlling for industry fixed effects.

Figure 6. Evolution of Firms' Total Factor Productivity



Sources: Worldscope and IMF staff calculations.
Note: Both Panel 1 and 2 use a balanced firm sample from 2015 onwards that includes publicly listed firms in the US and 15 advanced economies in Europe (AUT, BEL, DEU, DNK, ESP, FIN, FRA, GBR, GRC, IRL, ITA, LUX, NLD, PRT and SWE). Averages are weighted by sales. In panel 2, countries included in REST are AUT, BEL, DNK, ESP, FIN, GRC, IRL, ITA, LUX, NLD and PRT. Data labels use International Organization for Standardization (ISO) country codes.

Focusing on the evolution of within-firm TFP growth, regression analysis suggests that within-firm TFP growth in 2021 was relatively larger for the ex ante more digital-intensive firms. For the case of the US, the analysis, which follows the approach of Duval, Hong, and Timmer (2020), controls for state-industry fixed effects and key observable firm characteristics (including firms' age and pre-pandemic size and profitability). The controls included imply the comparison of similar firms within the same state and industry that differed in their degree of pre-pandemic digital intensity and confirm that the productivity of firms that were more digitalized ex ante grew at an increased rate (relative to their pre-pandemic average) more than less digitalized firms. For 2020, regression results suggest that the impact of ICT preexposure was not statistically different from zero in the US (Figure 7, panel 3).[12] A similar regression analysis for advanced Europe (which exploits variation of pre-pandemic digital intensity at the sector-country level) yields comparable results (Figure 7, panel 3). In both regions, ICT pre-adoption helped firm productivity recover faster from the crisis in 2021.

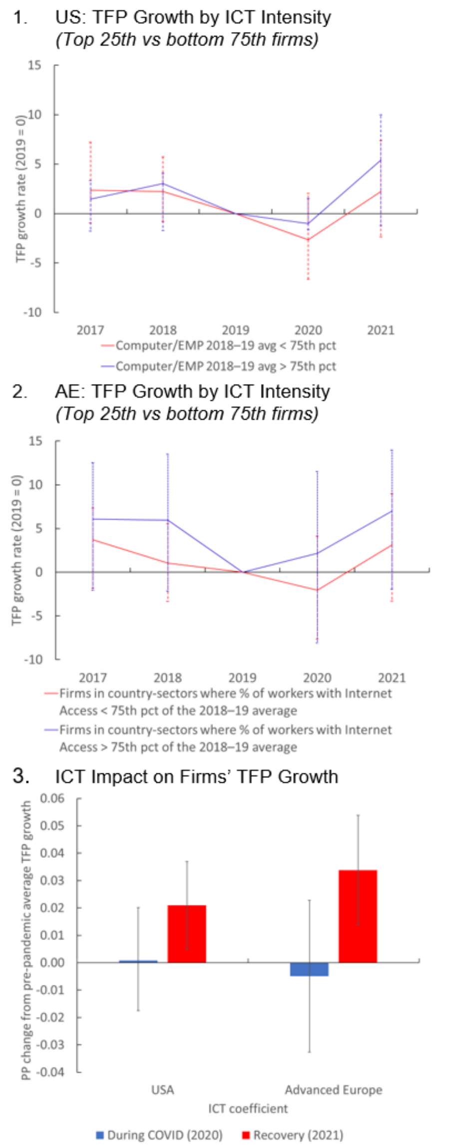
The TFP results for publicly listed firms in the US thus provide stronger evidence of lasting benefits from digitalization than the sectoral labor productivity evidence so far. However, many factors can explain the difference in results between labor productivity and firms' TFP. These include the fact that

[12] Annex 3.2 provides further details on the regression analysis. For the US, variation of pre-pandemic ICT intensity at the firm level is exploited (using Worldscope). The measure of ICT intensity is the log of deflated computer equipment and software assets over workers. For the European sample, the measure employed is the pre-pandemic average of the share of workers with computers that have internet access at the country-sector cell.

labor productivity changes are driven by factors beyond TFP (for example, changes in level and composition of employment) and that publicly listed firms are a subset of all firms that are larger. Larger firms may be able to leverage their investments in digitalization more thanks to economies of scale and network effects brought about by digitalization.

Historically, increases in digitalization are associated with increases in firms' TFP (Borowiecki and others 2021). To gauge the potential long-term impact that the COVID-19 digitalization push could have in the economy, an analysis of the long-term relationship between digitalization and firms' productivity is conducted using an unbalanced panel of US publicly listed firms from 2011 to 2019. Following Borowiecki and others (2021), firm TFP growth is regressed on the frontier firms' (defined as firms in the top 5 percent of the productivity distribution for each sector and year) TFP growth, the lagged gap between TFP for frontier and remaining firms, the lagged firm-specific digitalization measure, and firm-level controls (including for age and size of the firm) as well as sector and year fixed effects. The main results from this empirical exercise indicate that historically a 10 percent increase in the ratio of gross computer equipment and software assets to workers—which would correspond to twice the average yearly increase of the ratio in the sample—is associated with a 0.03 percentage point increase in TFP growth the following year and a cumulative 0.3 percentage point increase in long-term TFP, pointing to some potential benefits of digitalization, in line with previous studies (for example, Borowiecki and others 2021; Gal and others 2019).[13]

Figure 7. Firms' ICT Intensity Has Increased since 2019



Sources: Eurostat; Worldscope; and IMF staff calculations.
Note: Panel 1 and Panel 2 plot the TFP growth rate for high-ICT firms (in blue) and low-ICT firms (in red). High-ICT firms are defined as those at the top 25% of the 2018–2019 average ICT firm distribution in the US and country-sector in Advanced European countries and low-ICT firms are defined as firms at the bottom 75% of the ICT distribution respectively. ICT is defined as the log of the ratio of computer equipment and software to workers in the US and in Europe as the share of workers using a computer with internet access reported by the Eurostat. Countries included are AUT, BEL, DEU, DNK, ESP, FIN, FRA, GBR, GRC, IRL, ITA, LUX, NLD, PRT and SWE. Panel 3 plots the ICT coefficient from regressing the within-firm gap between the TFP growth in 2020 and 2021 and pre-COVID TFP growth average for a sample of US and Advanced European publicly listed firms. In all bar charts, the ICT coefficient is multiplied with the ICT standard deviation.

IV. Labor Markets

The rapid increase in digitalization may have profoundly affected labor markets, through overall employment but also the composition of labor demand. In the short term, digital technologies allowed a greater resilience of the labor market during the pandemic by enabling many workers to switch to work from home. Working from home could also lead to less scarring from the pandemic on employment in

[13] For details on the empirical specifications see Annex 3.2. The results show no statistical significance for the coefficient on the contemporaneous digitalization, in line with new technologies' implementation lags. Results should not be interpreted as causal effects; while the lagged digitalization helps address reverse causality concerns, omitted variables remain an issue. Results remain statistically significant in a two-stage least squares specification where firms' exposure to sector-wide digitalization is used as an instrument for firm-level digitalization, mitigating endogeneity concerns.

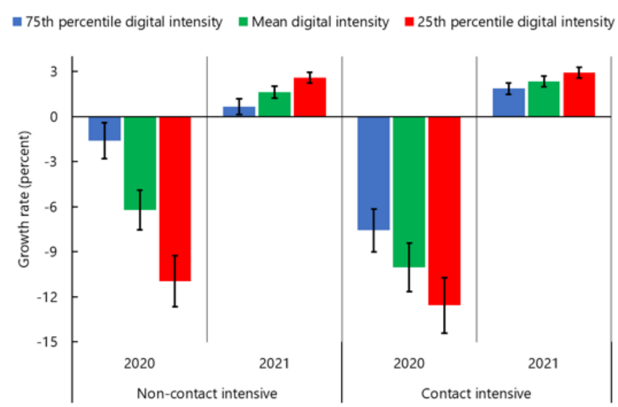
the longer term and transform where and when workers can perform their jobs, ultimately boosting workers' labor supply. Digitalization, however, may have permanently shifted the composition of labor demand toward workers with higher digital skills. This section investigates these issues.

IV.1 Digitalization and Sectoral Employment

Digitalization played a role in protecting hours worked at the height of the pandemic. The analysis performed here is like the one done to appraise the impact of digitalization on sectoral and aggregate labor productivity (see Section III). It shows that in addition to sustaining labor productivity, digitalization supported total hours worked in 2020, and even more so in non-contact-intensive sectors. Taking the point estimate at face value, for a high level of digitalization of the sector (75th percentile) relative to a low level of digitalization (25th percentile), sector-level losses in hours worked would have been 85 percent smaller among non-contact-intensive sectors and 40 percent smaller in contact-intensive ones (Figure 8).[14,15] At the aggregate national level, countries with low levels (that is, below median in 2019) of digitalization could have reduced losses in hours worked by slightly more than one-third of the total contraction if their sectors had digitalization levels equal to the 75th percentile of digitalization observed within each sector in the sample.

Figure 8. Regression Results on Total Hours Worked

(Predicted growth of hours worked by high, mean, and low digital intensity in response to the Google mobility shock)



Sources: Eurostat; Organisation for Economic Cooperation and Development; and IMF staff calculations.
Note: The figure plots a linear combination of the estimated regression coefficients representing the predicted growth rate of hours worked, in a country experiencing an average change in mobility, for a sector with high (75th percentile), average, or low (25th percentile) digital intensity based on the sector-adjusted distribution (i.e., abstracting from differences across sectors in the average level of digitalization), separately for non-contact intensive and contact-intensive sectors. Country sample: AUT, BEL, CZE, DEU, DNK, ESP, EST, FIN, FRA, GBR, GRC, IRL, ITA, LTU, LUX, LVA, NLD, NOR, PRT, SVK, SVN, SWE. Annex 4 describes the regression specification and the data in detail.

Overall, digitalization may have helped keep workers more attached to the labor market throughout the pandemic. While employment in low-digital sectors rebounded in 2021, higher levels of digitalization overall reduced the negative impact of the pandemic on hours worked over the two years. The labor market tightness in sectors predominantly employing lower-skilled workers seen in 2021 (Duval and others 2022) reflects in part firms' need to rehire workers separated during 2020. Low digitalization in some of these sectors may have thus contributed to labor shortages experienced during the recovery.

[14] The coefficient on the interaction term is only significant at the 10 percent level and when country-level population weight is used, suggesting that the result is driven by larger European countries.

[15] As governments in many European economies enacted broad-based job retention programs to reduce job destruction during the pandemic, the majority of the contraction in total hours worked is driven by the intensive margin (that is, hours per worker) rather than the extensive one (that is, total number of workers). Hence, focusing total hours would provide a full picture of changes in total labor input over the period.

IV.2 Digital Occupations

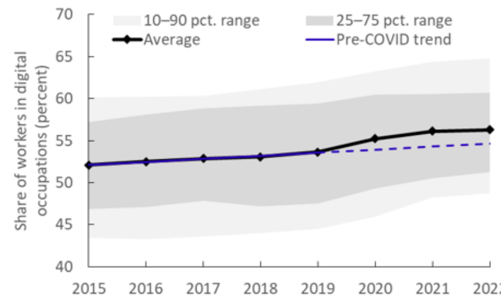
To better understand the impact of the COVID-19 digitalization on the composition of employment and labor demand, this note uses data on occupations and defines digital occupations based on knowledge and importance of using computers from O*NET.[16] Examples of occupations with high digital scores include computer programmers and software developers, while those with medium digital scores include tax preparers, hotel desk clerks, and nurse practitioners. Those with low digital scores (defined as non-digital occupations) include carpet installers and painting and coating workers. This score captures the digital content of tasks performed in a job, overlapping with but going beyond other features often discussed in the literature such as "teleworkability" (that is, the ability to perform a job remotely) and task intensity (that is, whether the job is predominantly manual or cognitive, and whether it involves routine tasks).[17]

The share of digital occupations in employment has grown during COVID-19.[18] Using a coarse occupation category (ISCO08 1 digit), the employment share of digital occupations has increased over time, and its increase has accelerated above trend during the COVID-19 pandemic (Figure 9, panel 1). Moreover, countries with a lower initial share of digital occupations in 2015 did not see annual average increases in digital employment before COVID-19 but have seen a catch-up during the COVID-19 period, as shown by the negative relationship between the initial level of digital employment share in 2015 and the average annual growth in digital employment share post–COVID-19 over 2019–22 (Figure 9, panel 2).

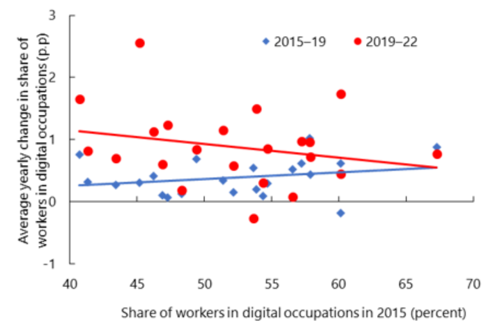
However, the degree of digitalization is heterogeneous across countries. While most countries have experienced an increase above trend in the share of digital employment, a few countries saw a decline relative to trend (Figure 9, panel 3). For example, Portugal, a country with low digital intensity and a small share of digital workers has seen the fastest acceleration in digital employment share during the COVID-19 pandemic. However, Denmark, which already had a high share of digital

Figure 9. Digital Occupations

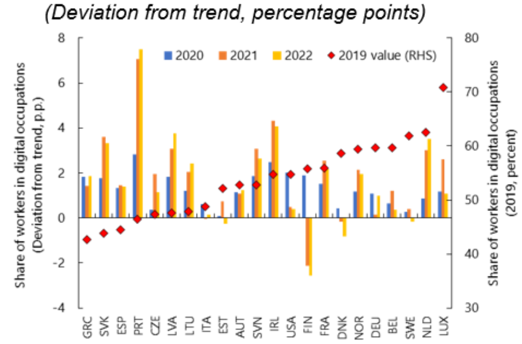
1. Trends in Employment in Digital Occupations
(Deviation from 2015–19 trend)



2. Catching Up within Digital Occupation Shares
(Average annual change, percentage points)



3. Cross-country Employment Share in Digital Occupations
(Deviation from trend, percentage points)



Sources: Eurostat; US Current Population Survey; and IMF staff calculations.
Note: Country sample: AUT, BEL, CZE, DEU, DNK, ESP, EST, FIN, FRA, GRC, IRL, ITA, LTU, LUX, LVA, NLD, NOR, PRT, SVK, SVN, SWE, USA. Data labels use International Organization for Standardization (ISO) country codes.

[16] Each occupation in O*NET is assigned a digital score based on workers knowledge of and frequency of use of computers in their work. Occupations with digital scores above the 50th percentile are classified as digital and those below the threshold as non-digital. The classification is described in Soh and others (2022), adapting the original methodology of Muro and others (2017). Digital occupations are highly correlated with digitalization measures used in Section II as shown in Annex Figure 1.1.

[17] See Soh and others (2022) for a detailed discussion of the overlap and differences in these categorizations.

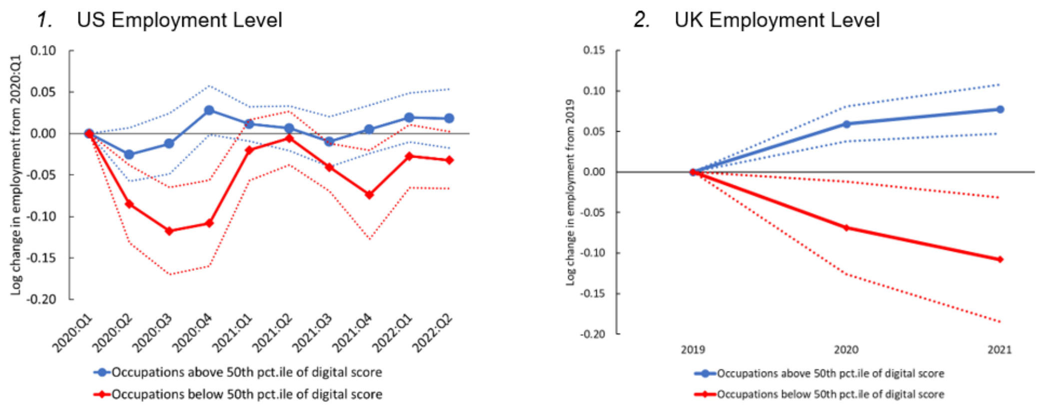
[18] See Annex 1 for a details on the classification of occupations as digital and non-digital.

employment prior to COVID-19, did not see a sustained increase in its share. In the case of Finland, the share of digital employment has declined sharply relative to trend.

Regression analysis suggests that COVID-19 induced only a temporary "shielding" of employment in digital occupations in some countries but a more persistent increase in such employment in others. The analysis uses granular data and cross-regional variation in the exposure to COVID-19. It regresses the levels of employment in digital and non-digital occupations within a region on a variable proxying for the region's exposure to COVID-19, interacted with dummy variables for different periods to capture time variation.[19] Figure 10 reports the estimated coefficients of the "COVID shock" variable for different time periods.

In the US, the analysis suggests that states that were more adversely affected by COVID-19 saw a larger but temporary rise in the share of digital occupations throughout 2020–21 originating from a "shielding" effect. While the effects of the region's exposure to COVID-19 for non-digital occupations are negative and large, those for digital occupations are just barely negative and not statistically significant (Figure 10, panel 1). The gap between the two sets of coefficients suggests that digital occupations experienced a shallow contraction but not a rise in absolute term. Moreover, the coefficients indicate that non-digital employment rebounded fast in the second half of 2021 in hard-hit regions.[20]

Figure 10. Regression Analysis of the Effect of COVID-19 on Employment in Digital and non-Digital Occupations



Sources: UK: Office of National Statistics Annual Population Survey; US: Current Population Survey, Quarterly Workforce Indicators, American Community Survey, Job Openings and Labor Turnover Survey; and IMF staff calculations.
Note: Panels 1 and 2 report the estimated regression coefficients for the period dummy variable interacted with a measure of economic exposure to COVID-19 at the regional level for the US (panel 1) and the UK (panel 2). The dependent variable is the change in level of employment in digital and non-digital occupations since the corresponding quarter in 2019 for the US and the average for 2019 for the UK. Details of the COVID-19 exposure variable for each country are provided in the main text and in Annex 4. Both variables are scaled to have a one-unit difference between the 10th and the 90th percentile. Hence, the coefficient shows the differential change in the digital employment share in hard-hit regions (90th percentile) relative to less hit regions (10th percentile) in a period. Annex 4 describes the regression specification and the data in detail.

In the UK, the analysis suggests a large and persistent differential effect of COVID-19 on the employment share of digital occupations coming from a mild rise in digital employment and a more persistent fall in non-digital employment in harder-hit areas (Figure 10, panel 2). These results should be placed into the context of the employment protection policies enacted in the UK. Throughout 2020 and early 2021, a higher share of workers in non-digital occupations than in digital ones were covered by the Coronavirus Job Retention Scheme (CJRS) (Annex Figure 1.2.1), suggesting that the program likely prevented job displacements in the former group to a larger extent and that, without the scheme, the increase in the share

[19] See details on the construction of the shock Details in Annex 4.

[20] The analysis uses the 50th percentile of the O*NET digital score as the baseline threshold for defining digital occupations. Further analysis for the US using the same regression approach is presented in Soh and others (2022).

of digital employment would have likely been even larger (Annex Figure 1.2.2).[21] As the economy recovered, the share of workers under the CJRS declined until the program's phaseout date.

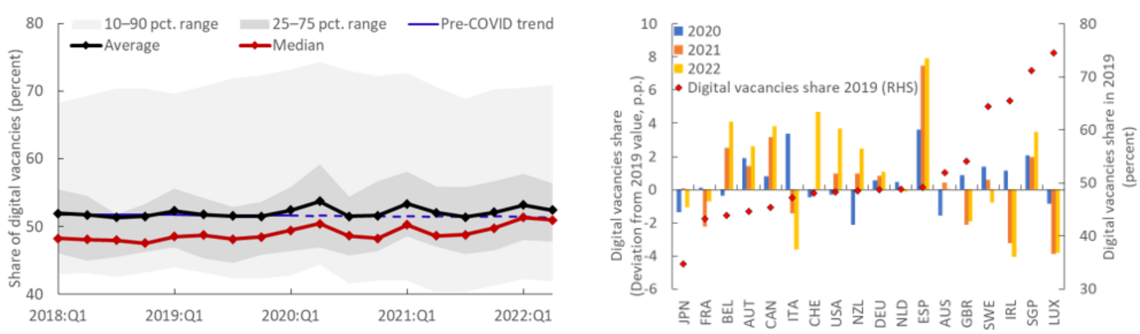
IV.3 The Impact of COVID-19 on Digital Labor Demand

To identify the impact of digitalization on labor demand, we use vacancies data from Indeed, a large online aggregator of job advertisements operating in multiple countries. Employment dynamics, examined in the previous section, result from both the separations of incumbent workers from their jobs and the creation of new jobs. Hence, the evolution of the share of employment in digital occupations over time is the outcome of confounding forces driving labor demand and labor supply. Vacancies, on the other hand, provide a more direct reflection of firms' demand for different types of occupations and can be a more forward-looking indicator.[22] During the pandemic and in the subsequent recovery, a shift in the composition of vacancies toward digital occupations may have occurred if firms progressively transitioned toward a more remote-based work environment.[23]

Figure 11. Share of Vacancies in Digital Occupations in Advanced Economies

1. Share of Vacancies in Digital Occupations *(2018:Q1–22:Q2)*

2. Share of Vacancies in Digital Occupations by Country *(Deviation from 2019 avg.)*



Sources: Indeed and IMF staff calculations.
Note: Country Sample for Panel 1 is AUS, AUT, BEL, CAN, CHE, DEU, ESP, FRA, GBR, IRL, ITA, LUX, NLD, NLZ, JPN, SGP, SWE, USA. Data labels use International Organization for Standardization (ISO) country codes.

The increase in the share of digital vacancies is less pronounced and more heterogeneous across countries than for employment. Data from Indeed across multiple advanced economies show that the share of vacancies for digital occupations increased only slightly since 2020 in the average country (Figure 11, panel 1).[24] The share of vacancies is also very heterogeneous across countries (Figure 11,

[21] As in Cribb and others (2021) and Pizzinelli and Shibata (2023), in the Labour Force Survey, workers are classified as covered by the CJRS if they are employed but were away from work in the reference week either because their work was "interrupted by economic causes" or for "other" reasons.
[22] During the COVID-19 recovery period, some of the increase in vacancy postings could reflect higher quit rates for certain occupations. While the analysis in this section focuses on the *composition* of vacancies, Duval and others (2022) show that in advanced economies the total *level* of vacancies contracted sharply during the first quarters of the pandemic and subsequently recovered at a fast pace, reaching above pre-COVID levels by late 2021.

[23] A compositional shift toward digital occupations could occur if employment in digital occupations suffered a larger rise in quits and firms posted vacancies to replace the separated workers. This channel is inconsistent with the employment analysis, showing that workers in digital occupations experienced a small contraction or a rise in employment in 2020. Further evidence is presented in Soh and others (2022) using data on job quits.

[24] Digital vacancies are defined based on "normalized categories" (norm-cats) that are created by Indeed. Annex 1.5 shows how we classify norm-cats into digital and non-digital and data availability. While the coverage of online postings is not representative of all vacancies in the economy, Adrjan and others (2021) find that the time variation in vacancies within occupations tracks well that of series produced by national statistical offices.

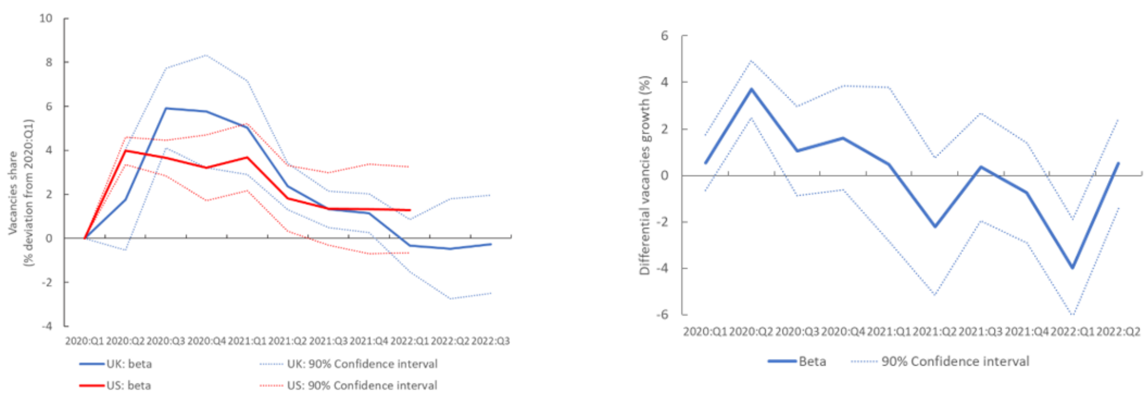
panel 2). While the digital vacancy share rose by 5 percentage points in Spain by 2022, it declined in France, the UK, Italy, Ireland, and Luxembourg—falling by about 5 percentage points in the latter. Moreover, about half of the countries in the sample saw only a temporary increase in digital vacancies in 2020 and a reversal in 2021–22.

Cross-country regressions as well as region-level analysis for the US and UK provide further evidence of only a temporary, not permanent, increase in digital vacancies as a result of COVID-19. The cross-country analysis suggests that a larger exposure to COVID-19 was associated with a statistically significant temporary rise in the differential growth rates of vacancies for digital occupations during the second quarter of 2020 only (Figure 12, panel 2).[25] Exploiting cross-regional variation in the US and the UK yields a larger and more persistent impact of exposure to the pandemic, with the positive effect on the digital vacancies share on more exposed regions persisting through mid-2021 (Figure 12, panels 1). Nevertheless, by 2022 the differential impact had waned within both countries.

Figure 12. Regression Analysis of COVID-19 Exposure and Vacancies for Digital Occupations

1. Region-Level Regression: Vacancies Share

2. Cross-Country Regression: Vacancies Level



Sources: Indeed; UK Office of National Statistics; US Bureau of Labor Statistics; and IMF staff calculations.
Note: Panel 1 reports the estimated regression coefficients for the period dummy variable interacted with a measure of economic exposure to COVID-19 at the regional level for the US and the UK. The dependent variable is the change in the share of vacancies in digital occupations since the corresponding quarter in 2019. The exposure variable is a Bartik-type proxy based on pre-COVID industrial composition for the US and the drop in the Google Mobility Index for the UK. Both variables are scaled to have a one-unit difference between the 10th and the 90th percentile. Hence, the coefficient shows the differential change in the digital employment share in hard-hit regions (90th percentile) relative to less hit regions (10th percentile) in a period. Digital occupations are classified using as threshold the 50th percentile of the O*NET digital score. Panel 2 reports the cross-country regression using "norm-cats" to categorize digital and non-digital vacancies. The plotted estimated regression coefficients show the differential vacancy growth rates between digital and non-digital occupations in response to a 10 percent decline in the Google Mobility Index in a period. The country sample is AUS, AUT, BEL, CAN, CHE, DEU, ESP, FRA, IRL, ITA, JPN, LUX, NLD, NZL, and SWE. Annex 5 describes the regression specification and the data in detail.

Multiple channels may explain the resilience of labor demand for non-digital occupations.[26] First, as discussed in Duval and others (2022), the pandemic led to an increase in inactivity, particularly among older and less educated workers, resulting in labor shortages in industries and occupations where these demographic groups are employed, mostly non-digital occupations. In addition, the decline in the net inflows of migrant workers that took place in some countries during the pandemic further aggravated these shortages. Vacancies in these jobs grew rapidly as firms tried to cover the workforce shortfall. Second, the pandemic saw abrupt swings in consumption patterns. During the months of lockdowns,

[25] Using a similar Indeed data set on new online job postings for Canada, Bellatin and Galassi (2022) also show that when policies become more stringent, job postings in digital-related occupations fared relatively better than job postings in non-digital occupations, and Copestake, and others (2022) find also that digitalization has helped shield workers in Asia and EMDEs.

[26] Other studies have also found only a temporary impact of the pandemic on the economy. For example, Alcedo and others (2023), using data on e-commerce in 47 economies, find a significant transient increase in online spending as a share of total consumption during the pandemic; however, these effects have been dissipating over time.

households shifted their spending heavily away from some in-person services toward goods that could be purchased remotely and consumed at home. While relying heavily on e-commerce platforms and digital infrastructure, this shift may have also increased the demand for workers in manual-intensive jobs such as warehousing and food and package delivery.

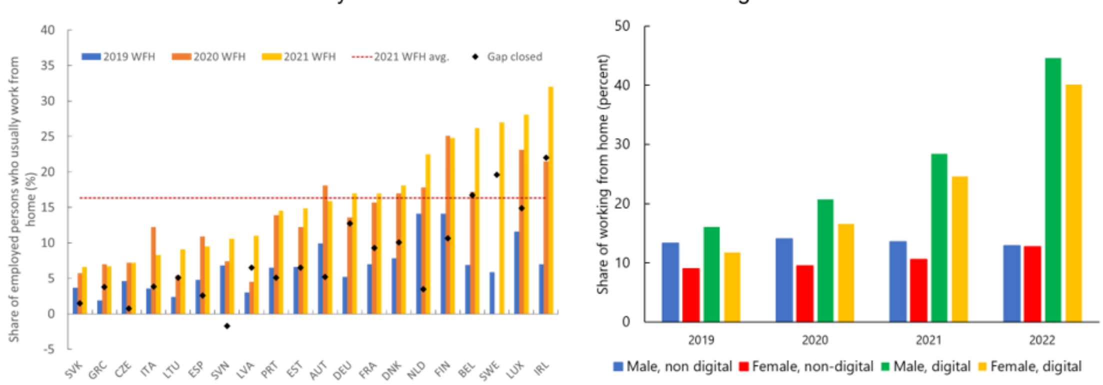
Last, there are no signs that the pandemic has impacted the "intensive margin" of digital employment by increasing the demand for digital skills within occupations.[27] Tracking the intensive margin is challenging because it requires a thorough measurement of the tasks workers perform within each occupation over time. Box 2 examines whether the digital intensity of work has increased during the pandemic, using data from LinkedIn. The analysis does not find evidence of an increase in the intensive margin of digitalization during the crisis. These findings are in line with Forsythe and others (2022), who found evidence of down-skilling after the pandemic as employers responded to increases in labor market tightness by relaxing skills and tenure requirements.

IV.4 The Effects of Digitalization on Labor Supply

The COVID-19 crisis has led to a significant and persistent increase in rates of work from home. Before COVID-19, only 5 percent of workers usually worked from home in Europe. In 2020 the share of workers working from home increased to 10 percent, and in 2021 to 16 percent. There are also significant differences across countries (Figure 13, panel 1). In 2021, in Greece, the share of workers teleworking increased to 7 percent, while in Finland, the percentage increased to 25 percent. These disparities partially reflect differences in the country's sectoral composition. A good indicator of work-from-home potential is the share of workers in teleworkable sectors. Among almost all countries in the sample, the gap between potential and actual rates of work from home has declined significantly following the COVID-19 crisis (Figure 13, panel 1). Yet there is still a significant gap, suggesting that further boosts in the percentage of workers working from home are possible.

Figure 13. Trends in Working from Home

1. Share of Workers Who Usually Work from Home
2. UK: Working from Home Trends



Sources: Eurostat; UK Labour Force Survey; and IMF staff calculations.
Note: The gap closed in panel 1 measures how much the gap between share of workers in teleworkable sectors and share of WFH workers was closed from 2019 to 2021. Panel 2 plots the share of workers who report working exclusively or mostly from home. Digital occupations are defined based on the 50th percentile of the O*NET digital score applied to the UK SOC 2010 classification. Values for 2022 are based on data up to Q3. Data labels use International Organization for Standardization (ISO) country codes.

[27] OECD (2019a, b) documents how digitalization affects the skills needed to perform different occupations.

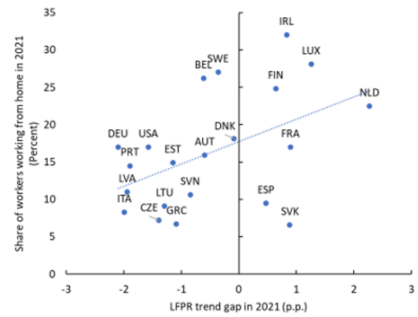
Recent evidence points out that workers highly value working from home. Working from home provides more flexibility in time use over the day, greater personal autonomy, and less time spent commuting, generating a significant amenity value for workers who can work from home. The value of these amenity gains can range from 1.5 percent of earnings at the low end of the earnings distribution to 7.3 percent at the high end (Barrero, Bloom, and Davis 2021). There is some evidence suggesting that these amenity gains help explain the lack of solid wage growth after the pandemic in the US despite labor market tightness (Barrero and others 2022) because workers acquire the implicit gains from working from home. The lack of wage growth is especially notable for high-skilled workers, while low-skilled workers, who are less likely to work from home, experienced wage gains, contributing to a recent decline in wage dispersion (Autor and Dube 2022).

By reducing the disutility from supplying labor, working from home could have positive consequences for employment in the longer term, although it is still too early to judge. Countries where a larger share of workers work from home have experienced a smaller drop in labor force participation and even an increase in labor force participation relative to the trend in 2021 (Figure 14, panel 1). The fact that this association is stronger in 2021 than 2020 suggests that the positive boost to labor force participation reflects not only digitalized workers' greater likelihood of remaining in employment during lockdowns and hence lower likelihood of leaving the labor force. It also suggests that workers value working from home and that working from home may increase labor force participation by attracting marginally attached workers and extending the working life of elderly workers.

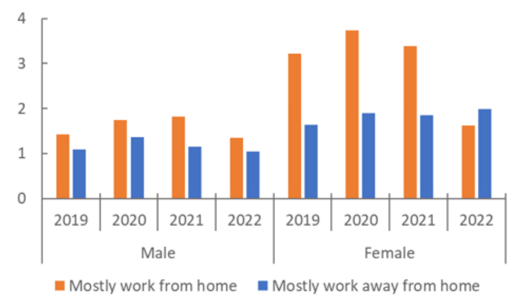
More direct evidence looking at the workers' transition rates from employment to inactivity also shows a growing positive impact of working from home. Workers' transition rates from employment to inactivity are shown by gender for the UK and the US, where more granular data are available, making a distinction based on whether individuals mostly work from home for the UK (Figure 14, panel 2) and whether workers worked at any point from home due to COVID-19 for the US (Figure 14, panel 3). In the UK, before the

Figure 14. Working from Home and Labor Force Attachment

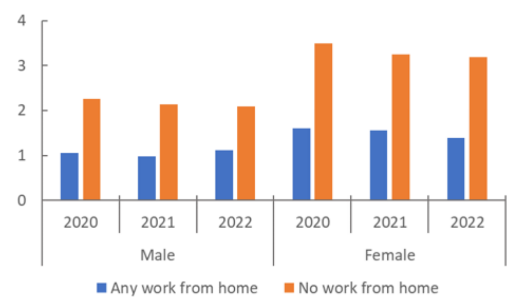
1. Changes in Labor Force Participation and Digitalization
(Labor force participation deviation from trend)



2. UK: Quarterly Transition Rate into Inactivity by Gender and Work from Home Frequency
(Percent)



3. US: Monthly Transition Rate into Inactivity by Gender and Work from Home Status
(Percent)



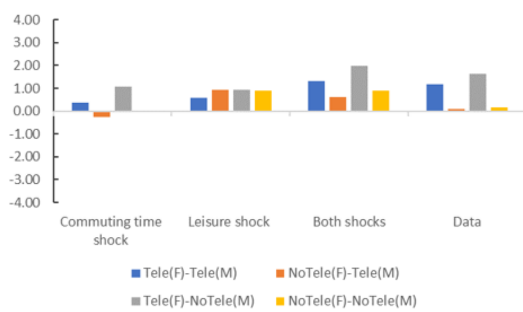
Sources: Eurostat; UK Labour Force Survey; US Current Population Survey; US Census; and IMF staff calculations.
Note: Panel 1 plots the gap in labor force participation in 2020 and 2021 relative to labor force participation trend estimated using 2015 to 2019 data. Panel 2 plots the probability that an employed worker transitions into inactivity (out of the labor force) from one quarter to the next. Values for 2022 are based on data up to Q3. Panel 3 plots the probability that an employed worker transitions into inactivity from one month to the next. Work from Home status is based on whether the respondent teleworked or worked from home for pay at any time during the four weeks prior to the survey due to the COVID-19 pandemic. Data labels use International Organization for Standardization (ISO) country codes.

pandemic, those working from home were more likely to leave the labor force than on-site workers, particularly among females. However, by 2022, this gap in the transition rate to inactivity shrank, suggesting greater labor force attachment among those working from home. Several channels may drive this shift. On the one hand, over time an increased preference to work from home, reflecting improved overall working conditions, may be increasing job retention. On the other hand, given the large rise in working-from-home arrangements, a substantial shift in the composition of those who work from home may have taken place. As shown in Figure 13, panel 2, the rise in working from home over 2019–22 was driven entirely by workers in digital occupations, who tend to be more highly educated and have greater labor market attachment. In the US, transition rates into inactivity were lower for both male and female workers who had previously worked from home due to COVID-19, suggesting positive consequences of working from home for labor supply also due to health concerns during the pandemic (Figure 14, panel 3).[28]

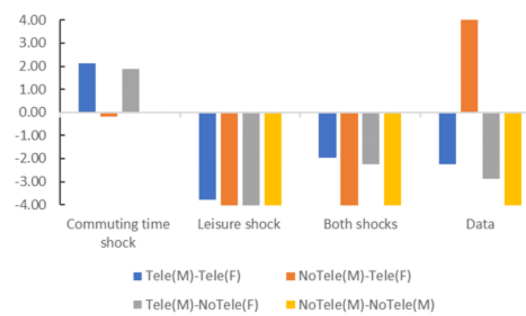
Time-use surveys suggest there may have been two shocks affecting labor supply as a result the pandemic. A critical benefit of working from home is the potential to save time commuting. Data from the American Time Use Survey (ATUS), which measures the amount of time people spend doing various activities, such as paid work, childcare, volunteering, and socializing, show that workers in teleworkable occupations save on average two hours a week by not commuting to an office.[29] Part of this savings is associated with an increase in working hours, particularly for women in teleworkable occupations. However, surprisingly, the savings in commuting time is associated with a decline in working hours for men in teleworkable and non-teleworkable occupations (right bars in Figures 15, panels 1 and 2). The reduction in men's working hours suggests that the pandemic may have increased men’s preference for leisure (independent of digitalization), leading to an acceleration in the long-term trend in men's decline in labor market attachment.[30]

Figure 15. The Labor Supply Implications of Working from Home

1. Female Changes in Hours Worked



2. Male Change in Hours Worked



Sources: American Time Use Survey (ATUS) and IMF staff calculations.
Note: Panel 1 and 2 present the results from the model simulation. Two different shocks are considered: (1) a shock that reduces commuting time among workers in teleworkable occupations (Tele), (2) a shock that increases men’s preference for leisure in teleworkable and nonteleworkable occupations (NoTele), and (3) a shock that combines shock (1) and (2). Panel 1 plots the changes in weekly hours worked for women and panel 2 for men.

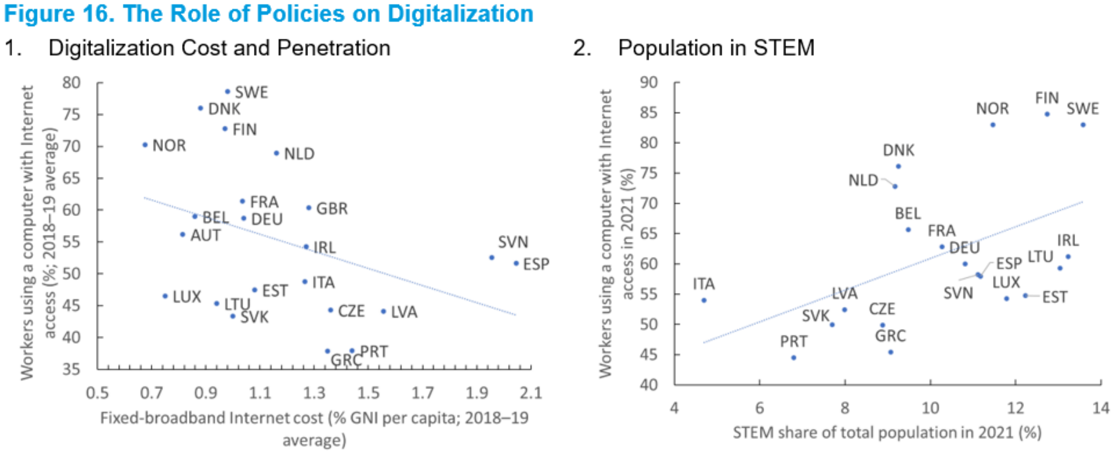
[28] In the UK Labour Force Survey, working from home may reflect several underlying factors. US data, however, capture whether the respondent worked from home specifically as a result of the COVID-19 pandemic.

[29] Aksoy and others (2023), surveying workers in a sample of 27 countries, find significant gains in commuting time from working from home. The same study finds that workers allocate 40 percent of their commuting time savings to their jobs.

[30] Ullrich (2021) points to multiple factors that can explain the decline in men's labor force participation in the US, including a shift in industrial structure, a reduction in male educational attainment, delayed family formation, a rise of substance abuse, incarceration, and heavy use of video games.

A modeling approach confirms that the pandemic may have affected labor supply through both lower disutility from working from home and an increase in the preference for leisure, especially for men. To disentangle the potential channels through which the pandemic may have impacted working hours, a model of household labor supply is developed (Annex 6 presents the model in detail). In the model a household consists of a husband and wife working in teleworkable or non-teleworkable occupations. A total of four households are simulated. The model is calibrated using data from the American Time Use Survey (ATUS). The model considers two shocks: (1) a decline in commuting time that impacts workers in teleworkable occupations and (2) an increase in the preference for leisure affecting men only. The main finding is that the decline in commuting time associated with remote work increases labor supply and leisure for workers in teleworkable occupations (Figure 15, panel 1). The increase in men's leisure preferences, on the other hand, leads to a decline in men's labor supply and an increase in women's labor supply due to the decline in family income. The final effect is that the model can replicate the increase in women's working hours and the decline in men's working hours (Figure 15, panel 2). The findings support the view that the increase in remote work improves welfare and will be associated with an increase in labor supply of workers in teleworkable occupations.

Figure 16. The Role of Policies on Digitalization



Sources: International Telecommunication Union; Organisation for Economic Cooperation and Development; and IMF staff calculations.
Note: Countries included in the chart are BEL, CZE, DEU, DNK, ESP, EST, FIN, FRA, GRC, IRL, ITA, LTU, LUX, LVA, NLD, NOR, PRT, SVK, SVN, and SWE. To get the STEM share of total population for each country, the note multiplies the STEM share of tertiary-educated population by the tertiary-educated population share of total population. Data labels use International Organization for Standardization (ISO) country codes.

V. Policy Recommendations

There are still significant cross-country differences in the cost of fixed and mobile broadband internet (Figure 16, panel 1). Countries with high internet costs have lower levels of digitalization. For example, the cost of fixed-broadband internet in Greece and Portugal is almost twice as high as in Norway, and the internet speed is slower. Bringing down the cost of internet can support small firms' adoption of basic and advanced technologies, particularly in the current context in which firms and households are facing increases in other costs of living.

Government policies can support a more digitalized economy by investing in digital infrastructure and by fomenting competition in the ICT sector. A modern digital infrastructure is needed to increase cybersecurity, access to the cloud, and data processing capabilities—and to provide good internet to all households, reducing the digital divide. Initiatives like the Next Generation EU Fund, an EU-wide program that provides funding to EU member states, aim to accomplish some of these objectives. Box A.1, in Annex 7, shows that less digitalized countries have the most ambitious digital transformation grant allocation proposals, suggesting increased efforts toward a digital catch-up. Ensuring competition between providers in the telecommunications sector would also help reduce the cost of digital services for users and increase access to digital technologies for small firms and poor households. In addition, governments should find the right balance between incentives to invest in productive digitalization versus stimulating excessive digitalization that accelerates the substitution of labor for capital (Acemoglu, Manera, and Restrepo 2020; Acemoglu 2023).

Competition policy must also evolve and adapt to the increase in market digitalization. Many digital markets are already highly concentrated and controlled by a few large firms (for example, search engines, social media platforms, and e-sales marketplaces).[31] The rise of new technologies (for example, big data and artificial intelligence) is multiplying incumbent firms' advantage discouraging innovation (Bessen 2022). Facilitating data portability and interoperability of systems can increase competition with established players. A precedent was set by the European Union that gave customers the right to keep their cell phone numbers when switching between operators in the early 2000s. As digital activities take up a larger share of the economy, it is imperative to establish fair, transparent, and inclusive competition practices to avoid winner-takes-all dynamics.

Besides investing in digital capital, governments should also invest in human capital. Equipping the workforce with the skills needed to perform higher-tech tasks will help sustain a more inclusive digitalized market. Among workers in highly digital occupations, 74 percent have a STEM degree, including master's and doctoral degrees. More digitalized countries also have a larger share of workers with a STEM degree, particularly with master's and doctoral education (Figure 16, panel 2). For example, in Portugal fewer than 8 percent of workers have postgraduate education in STEM, whereas in Sweden the number is almost 15 percent. Moving up on the digital ladder will require increasing the share of workers with digital skills.

Labor laws and regulations must also adapt to changing work environments to facilitate telework or remote work access. These new laws and regulations should seek to make telework attractive to workers and employers. Remote work legislation should strike the right balance between sometimes contradictory objectives, such as keeping workers accessible to firms while protecting work-life balance in a context of more flexible hours, protecting the privacy of workers while allowing firms to monitor their productivity, and sharing the cost of resources used to work from home.

VI. Conclusion

The COVID-19 pandemic has induced a digitalization push. The push is concentrated in contact-intensive sectors and among small firms, which started the crisis with relatively low levels of digitalization. Overall, less digitalized countries closed 20 percent of the gap with frontier-digitalization countries, but there remain large gaps in digitalization across countries, even controlling for differences in sectoral composition. The SDN has studied the consequences from the rapid digitalization shock, but with only two years of data one has to be careful in interpreting the significance and permanence of the results.

[31] Akcigit and others (2021) document the increase in corporate market power and discuss in detail how the design of competition policies can support more competitive markets.

Digitalization enhances the resilience of economies and could increase productivity in the longer term. Higher levels of digitalization were associated at the sector level with smaller losses in productivity and especially in employment in response to the pandemic shock. Because differences in digitalization remain large between countries for given sectors, they can explain a non-negligible part of the economic underperformance of less digitalized economies during the pandemic. In the longer term, historical evidence suggests that digitalization could lead to some gains in total factor productivity. However, whether smaller firms are able to reap the benefits from their investments in digitalization may depend on policies in place to ensure healthy competition in digital markets.

In the labor market, there is not much evidence of a structural shift in the composition of labor demand; however, changes in working from home appear persistent so far and could boost labor supply. Workers in digital occupations initially experienced fewer layoffs than other workers. However, the increase in the relative demand of digital workers reversed as mobility rebounded. This is consistent with the evidence that the COVID-19 digitalization push has led to catching up in the use of essential technologies rather than an increase in the investment in more advanced or revolutionary technologies. One trend that appears to be more permanent so far is the work-from-home revolution. The evidence suggests that workers value working from home, which saves commuting time and gives greater time management flexibility. By reducing the disutility associated with work, it increases attachment to the labor market and could potentially boost labor supply while increasing workers' welfare.

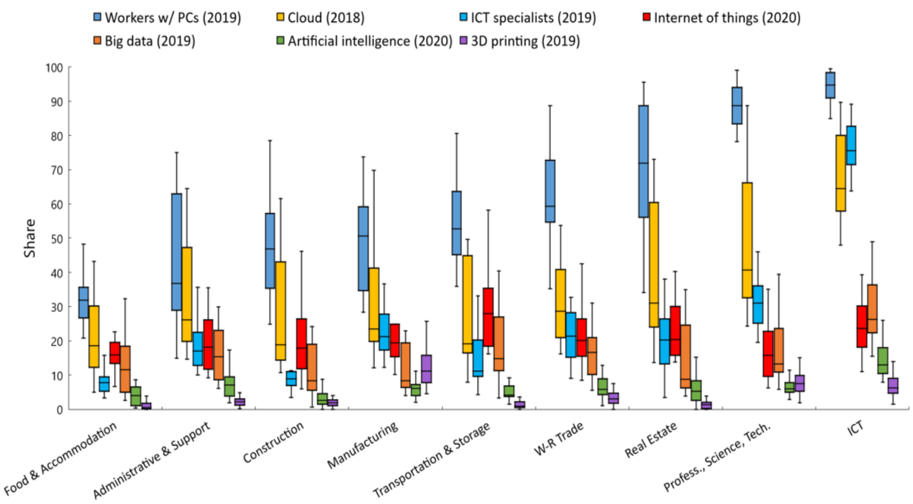
Government policies are still needed to bring low-digitalized countries close to their more digitalized peers and ensure that the gains from digitalization are broadly shared. The digitalization push has not been sufficient to close the digitalization gap across countries, although progress was achieved during the pandemic. In countries where digitalization remains low, investments in digital infrastructure and in education and training to equip workers with the right digital skills are needed. Competition among technology providers can help lower prices and increase the quality of services provided; ensuring healthy competition between technology users is also key to allow smaller firms to benefit from their investments in digitalization. Last but not least, adapting labor laws and regulations to the changing work environment will help facilitate and provide important safeguards for remote work.

Box 1. Alternative Measures of Digitalization[1]

The Eurostat Digital Economy and Society database provides multiple indicators of digital intensity. Data availability for these alternative measures is more limited in terms of country and time coverage than the share of workers using a PC with internet access, which serves as the baseline proxy for digital intensity in this note.

Nevertheless, comparing these additional measures at one point in time provides a more nuanced picture of digitalization across countries and sectors. Box Figure 1.1 summarizes the distribution of different digitalization measures by sectors across advanced European economies for the latest available data prior to the pandemic (or the earliest available data for two indicators) and compares them with the baseline measure. The alternatives considered are the share of firms that (1) purchase cloud services, (2) employ ICT specialists, (3) conduct "big data" analysis, (4) use the Internet of Things (IoT), (5) use artificial intelligence (AI), and (6) use 3D printing.

Box Figure 1.1. Alternative Digitalization Measures by Sector across Countries



Sources: Eurostat and IMF staff calculations.
Note: The middle bar and the upper and lower bounds of the box report the 50th, 25th, and 75th percentiles of the distribution of the measure across countries within each sector. The whiskers report the upper and lower adjacent values, which are the values furthest away from the median on either side but still within a distance of 1.5 times the interquartile range from the 25th and 75th percentiles, respectively. Country sample: AUT, BEL, CZE, DEU, DNK, ESP, EST, FIN, FRA, GBR, GRC, IRL, ITA, LTU, LUX, LVA, NLD, NOR, PRT, SVK, SVN, SWE, USA. ICT = information communication technology; W-R = wholesale and retail.

Several patterns emerge. First, alternative digitalization measures tend to have a low penetration in most sectors. The shares refer to firms while the baseline measure refers to workers, so they are not entirely comparable. However, the median share of workers using an internet-connected computer shows a marked gradual rise from the sector with lowest intensity (food and accommodation) to the one with the highest (ICT), with large variation across countries as well. On the other hand, while the ranking of intensity is generally consistent across indicators, most alternative measures do not show such pronounced differentials from sector to sector.

An intuitive reason for this difference in penetration is that the share of workers using a computer reflects a basic and widespread type of digital technology that is both multifunctional—and thus applicable to numerous productive activities—and potentially accessible to many workers. Conversely, the alternative measures refer to more advanced digital technologies with larger fixed costs that are mostly used in larger firms (as found by Acemoglu and others 2022). Hence, they are less appropriate to provide a wide-angle view of the use of digital technology at large in the production process within a sector or country. Furthermore, the share of workers using a computer can also be thought of as the upper bound for the use of other more advanced technologies within a sector. Intuitively, it would be challenging, and probably inefficient, for a firm to deploy cloud computing, big data analysis, or artificial intelligence if a larger fraction of its employees does not first use computers in their work.

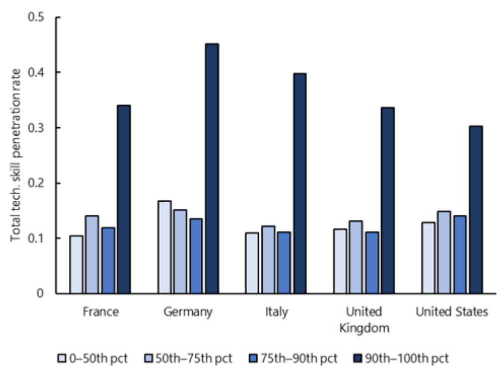
[1] Prepared by Carlo Pizzinelli.

Box 2. Measuring the Evolution of Digital Skills Using Data from LinkedIn[1]

The intensive margin of digital employment may have played a significant role during the pandemic if, within the same occupation, workers were asked to perform more digital tasks than they used to. For instance, an office assistant may need to handle audio-video equipment to set up hybrid remote–in-person meetings. On the other hand, it is also possible that the basic infrastructure adopted in low-digital-intensity sectors during the pandemic does not require the kind of advanced skills that workers would include in their resumes.

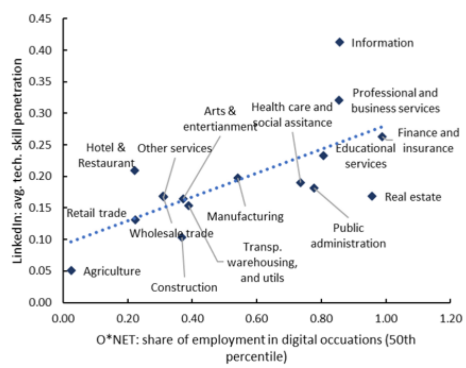
Tracking the intensive margin of digital work is challenging, because it requires a repeated measurement of the tasks workers perform within each job. However, the O*NET repository is only slowly updated over time. Facing this measurement challenge, skills reported by workers in their online profiles can provide a real-time proxy for changes in the functions they perform in their jobs. LinkedIn is a large online platform, present in numerous countries, where workers can apply for new positions as well as showcase their expertise and skills from their current job. Using a vast amount of data extracted from individual profiles, the LinkedIn Economic Graph and Research Insights team constructs a yearly measure of "tech skill penetration" rate for each job title, industry, and country.[2] This measure represents the fraction of job-specific skills reported by workers in a given year that pertain to digital technologies within an industry and occupation. It therefore serves as a "flow" measure of the degree to which technology skills are being updated within an industry and/or occupation.

Box Figure 2.1. Technology Skill Penetration Rate for Occupations in Different Ranges of the O*NET Digital Score



Sources: LinkedIn and IMF staff calculations.
Note: The different bars report the average technology skill penetration rate for 4-digit ISCO-08 occupations within each percentile range of the O*NET digital score. The rates are computed as the average values over 2017–21.

Box Figure 2.2. Skill Penetration and O*NET



Sources: LinkedIn; US Bureau of Labor Statistics; and IMF staff calculations.
Note: The x-axis reports the 2019 share of workers in digital occupations for each sector based on the 50th percentile threshold of the O*NET digital score. The y-axis reports the average technology skill penetration rate in 2020–21. See Annex 1 for details of the construction of industry-level average rates.

Box Figure 2.1 reports the average penetration rate for selected advanced economies during 2020–21. Each bar reports the penetration rate for a different group of occupations based on the O*NET digital score, from non-digital occupations (those with a score below the median) to digital occupations within different percentile ranges. Two notable results emerge. First, in all countries the penetration rate is roughly constant—close to 20 percent—across most occupations but is substantially higher for occupations with a very high O*NET score (above the 90th percentile). This suggests that jobs involving a high digital content also require frequent updating of relevant skills. Second, penetration rates within each group of occupations are very similar across economies, suggesting comparable degrees of technology skill updating. A key question is whether the pandemic encouraged significant updating or acquisition of technology skills in different industries. Box Figure 2.2 shows that for the US in 2020–21 skill penetration rates were higher in industries that already had larger shares of digital occupations. This result points to a limited impact of COVID-19 on the demand for digital skills within sectors with historically lower digitalization.

[1] Prepared by Carlo Pizzinelli.

[2] Annex 1 describes in detail LinkedIn's skill penetration measure, its construction, and caveats regarding its interpretation. See also Zhu, Fritzler, and Orlowski (2018) for a more general description of LinkedIn's data and its applications.

Annex 1. Data Sources, Sample Coverage, and Variable Definitions

1.1 Descriptive Charts – Aggregate Data

Data sources used for the descriptive charts in Sections I, II, and III are listed in Annex 1, Table 1.1.

Table 1.1. Data Sources for Stylized Facts

Figures	Sources	Economies
Figure 1: 1. Trends in Labor Productivity across countries and sectors; 2. Labor Market Tightness (V/U)	Eurostat, US Bureau of Economic Analysis and Bureau of Labor Statistics, UK Office of National Statistics	1.1: AUT, BEL, CZE, DEU, DNK, ESP, EST, FIN, FRA, GBR, GRC, IRL, ITA, LTU, LUX, LVA, NLD, NOR, PRT, SVK, SVN, SWE, and USA.
Figure 2: 1. Workers using a computer with internet access; 2. Digitalization by country; 3. Digitalization by firm size; 4. Digitalization by sector; 5. Decomposition of cross-country differences in digitalization; 6. Decomposition of change in digitalization	Eurostat, International Telecommunication Union	BEL, CZE, DEU, DNK, ESP, EST, FIN, FRA, GRC, IRL, ITA, LTU, LVA, LUX, NLD, NOR, PRT, SVK, SVN, and SWE;
Figure 3: 1. Software spending per employee by sector; 2. Share of small firms and growth in software spending by sector; 3. Firm-level computer equipment and software per worker; 4. Change in firm-level computer equipment and software per worker	Worldscope, US Census Bureau Annual Survey of Manufactures and Service Annual Survey	USA
Figure 4: 1. Labor Productivity and Digitalization across countries	Eurostat, UK Office of National Statistics, Bureau of Economic Analysis and Bureau of Labor Statistics	AUT, BEL, CZE, DEU, DNK, ESP, EST, FIN, FRA, GBR, GRC, IRL, ITA, LTU, LUX, LVA, NLD, NOR, PRT, SVK, SVN, SWE, and USA
Figure 6: 1. Firms' productivity trend; 2. Firms' productivity by country	Worldscope	AUT, BEL, DEU, DNK, ESP, FIN, FRA, GBR, GRC, IRL, ITA, LUX, NLD, PRT, SWE, and USA
Figure 7: 1. USA: Top 25 vs bottom 75th by Computer/workers share; 2. Advanced Europe: Top 25 vs bottom 75th by share of workers with Internet access	Worldscope, Eurostat	AUT, BEL, DEU, DNK, ESP, FIN, FRA, GBR, GRC, IRL, ITA, LUX, NLD, PRT, SWE and USA
Figure 9: 1. Trends in Employment in Digital Occupations; 2. Catching up with in digital occupation shares; 3. Cross-country employment share in digital occupations	Eurostat, Current Population Survey (USA)	AUT, BEL, CZE, DEU, DNK, ESP, EST, FIN, FRA, GRC, IRL, ITA, LTU, LUX, LVA, NLD, NOR, PRT, SVK, SVN, SWE, and USA
Figure 11: 1. Share of vacancies in digital occupations for selected countries; 2. Share of vacancies in digital occupations for selected countries	Indeed	AUS, AUT, BEL, CAN, CHE, DEU, ESP, FRA, GBR, IRL, ITA, LUX, NLD, NLZ, JPN, SGP, SWE, and USA
Figure 13: 1. Share of Workers Who Usually Works from Home; 2. US: Change in WFH between 2019 and 2021 by Workers' Characteristics; 3. Gap between potential and effective teleworkability; 4. UK: WFH Trends	Eurostat, UK Labour Force Survey	AUS, BEL, CZE, DEU, DNK, ESP, EST, FIN, FRA, GBR, GRC, IRL, ITA, LTU, LUX, LVA, NLD, NOR, PRT, SVK, SVN, and SWE
Figure 14: 1. Changes in labor force participation and digitalization 2. UK: Quarterly	Eurostat, UK Labour Force Survey, US	BEL, CZE, DEU, DNK, ESP, EST, FIN, FRA, GBR, GRC, IRL, ITA, LTU,

transition rate into inactivity by gender and work-from-home frequency (percent); 3. US: Monthly transition rate into inactivity by gender and work-from-home status (percent)	Current Population Survey, US Census	LUX, LVA, NLD, PRT, SVK, SVN, SWE, and USA
Figure 15: 1. Female change in hours worked; 2. Male change in hours worked	American Time Use Survey	USA
Figure 16: 1. Digitalization Cost and Penetration; 2. Population in STEM	International Telecommunication Union,Organisation for Economic Cooperation and Development	BEL, CZE, DEU, DNK, ESP, EST, FIN, FRA, GRC, IRL, ITA, LTU, LUX, LVA, NLD, NOR, PRT, SVK, SVN, and SWE

1.2 Digital Intensity Data

Eurostat

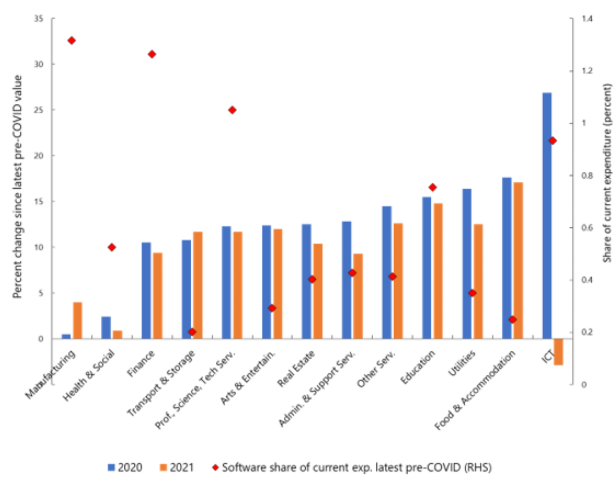
Data on digitalization by sector in advanced European economies used for the stylized facts in Section II and Box 1 are from Eurostat's online Digital Economy and Society Database. The version of the data used in this note, however, was downloaded from OECD Stat, the OECD's data platform, under the section Information and Communication Technology. The baseline measure of digitalization, also used throughout the note in combination with other data sources, is the share of workers using a computer connected to the internet. Other measures, discussed in Box 1, measure the share of firms that (1) purchase cloud services, (2) employ ICT specialists, (3) conduct "big data" analysis, (4) use the Internet of Things (IoT), (5) use artificial intelligence (AI), and (6) use 3D printing.

US Census

The stylized facts presented in Figure 3 use data from two sector-level surveys from the US Census Bureau. The Annual Survey of Manufacturers (ASM) is used for the manufacturing sector, while the Service Annual Survey (SAS) is used for all other sectors in the figures. While sector-level data tabulations available on the US Census website contain several items related to digital expenditure (e.g., investment spending on ICT, current spending on data services), the only item that is comparable across surveys is current expenditure on software. A similar sector-level survey for wholesale and retail trade exists but does not contain information on software spending. Hence these two industries, as construction, mining, utilities, and agriculture, are not included in the analysis. As the surveys

Annex Figure 1.1. US: Software Spending by Sector

(Percent change from latest available pre-COVID level)



Sources: US Census Bureau Annual Survey of Manufactures; US Census Bureau Service Annual Survey; and IMF staff calculations.
Note: The latest available pre-COVID year of data is 2019 for manufacturing and 2017 for all other sectors. The percentage changes from the pre-COVID period to 2020 are turned into annual rates for comparability. The variable on the RHS y-axis is the percent change in total software spending (at constant prices) while the variable on the LHS y-axis is the share of software expenditure as a share of total current expenditure in the sector.

also have different time coverage prior to 2020, the latest pre-COVID year available is 2019 for manufacturing and 2017 for the services sectors. To improve comparisons over the differing time spans, growth rates from the pre-COVID period to 2020 and 2021 are annualized. Data on the share of small firms in each sector in 2019, used in Figure 2.2, are from the US Census' annual data series titled Statistics of US Businesses. To strive for comparability with the Eurostat data in Figure 1, small firms are defined as those with 10 to 100 employees. Firms with fewer than 10 employees, known as "micro-firms" are excluded because the Eurostat statistics on digitalization survey businesses with more than 10 employees.

While Figure 3 focuses on software spending per employee, Annex Figure 1.1 shows that similar results emerge when considering sectors' total software spending.

1.3 Productivity Data

Country- and sector-level labor productivity

Country- and sector-level real labor productivity series used in Section III are computed as real output per hour worked. The raw data, compiled by national statistical offices, is downloaded from Eurostat for advanced European countries in the European Union, from the UK Office of National Statistics for the UK, and from the Bureau of Economic Analysis and Bureau of Labor Statistics for the US.

Worldscope database

This note uses the financials at an annual frequency from the Worldscope database by Refinitiv to estimate firm-level TFP (total factor productivity) for 16 advanced economies and firm-level ICT (information and communications technology) intensity for the United States only. The inputs for the TFP estimation are net sales, property, plant & equipment, and costs of goods sold. The note uses the ratio of computer software and equipment to property, plant & equipment to proxy for the firm-level ICT intensity for the publicly traded firms in the United States. Unfortunately, this ratio is rarely populated in the Worldscope database for advanced European economies. The note also considers other financial variables such as total assets and EBITDA to account for the variations in firm characteristics.

Firm-level total factor productivity data

The firm-level TFP data cover the period 2005 to 2021 at an annual frequency for 16 advanced economies including Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, The Netherlands, Portugal, Spain, Sweden, the United Kingdom, and the United States.

The note uses the annual financial data from the Worldscope database (only covers publicly traded firms) and follows Díez, Fan, and Villegas-Sánchez (2021) to estimate firm-level TFP. Under the assumption that firms within an industry share the same technology, an industry-specific Cobb-Douglas production can be estimated:

$$q_{it} = \beta_v v_{it} + \beta_k k_{it} + \omega_{it} + \epsilon_{it}$$

where all variables are in logs, q_{it} denotes the log of real sales, v_{it} is the log of real variable input, k_{it} represents the log of real capital stock, ω_{it} refers to productivity, and ϵ_{it} stands for the error term that includes measurement error and unexpected shocks. β_v represents the output elasticity of the variable input and β_k denotes the output elasticity of capital. Upon estimating the input-output elasticity, the firm-level productivity estimates can be recovered as residuals with available firm-level financials. The usual endogeneity concern consists of the potential simultaneity bias resulting from the possibility of correlation between the input choice and the productivity. Following Díez, Fan, and Villegas-Sáchez (2021), the methodology addresses this concern through the control function approach by assuming that the demand for the variable input, v, depends on productivity: $v_{it} = f(\omega_{it}, k_{it})$. Inverting it yields $\omega_{it} = f^{-1}(v_{it}, k_{it})$ and thus the production function can then be written as follows:

$$q_{it} = \beta_v v_{it} + \beta_k k_{it} + f^{-1}(v_{it}, k_{it}) + \epsilon_{it} = \phi(v_{it}, k_{it}) + \epsilon_{it},$$

where ϕ can be estimated using any consistent non-parametric estimator. In the second stage, the method assumes that productivity follows a first-order Markov process: $\omega_{it} = E(\omega_{it}|\omega_{it-1}) + \xi_{it}$, where ξ_{it} stands for an innovation shock to the productivity process. Then solving for ξ_{it} and replacing ω_{it} with the first-stage estimates can have:

$$\hat{\xi}_{it} = \hat{\phi}_{it} - \beta_v v_{it} - \beta_k k_{it} - \hat{E}(\hat{\phi}_{it-1} - \beta_v v_{it-1} - \beta_k k_{it-1})$$

With standard GMM procedures, β_v and β_k can be recovered. By assuming that the variable input v responds to current productivity shocks but its lagged values do not, the following moment condition can be formed:

$$E\begin{pmatrix}\xi_{it} v_{it-1} \\ \xi_{it} k_{it}\end{pmatrix} = 0,$$

from which β_v and β_k can be obtained. Finally, the firm-level productivity using the Worldscope database can be calculated as follows:

$$tfp_{c,i,t} = sales_{c,i,t} - \hat{\beta}_v cogs_{c,i,t} - \hat{\beta}_k ppe_{c,i,t},$$

where the index c refers to firm, all variables are in log form and all financial variables are in real terms.

1.4 Labor Force Data

US Labor Force Survey (Current Population Survey)

For detailed analysis of the United States in Section IV, the note uses two data sources: the Current Population Survey (CPS) issued jointly by the US Census Bureau and the US Bureau of Labor Statistics (US BLS) and the Job Openings and Labor Turnover Survey (JOLTS) issued by US BLS. CPS is a nationally representative monthly survey for the United States. The note calculates the stock of employed workers, unemployed, and those not in the labor force by the industry as well as flows between these labor force statuses at a monthly frequency between January 2000 and October 2021. The note uses vacancies (in levels), hires (in levels), and quit rates for the aggregate US economy and 17 industries based on the North American Industry Classification System (NAICS) between December 2000 and November 2021.

UK Labor Force Survey data

The note uses two data sources on the UK labor force. Worker-level micro data from the quarterly Labour Force Survey are used for the analysis of work from home and to compute the share of workers covered by the

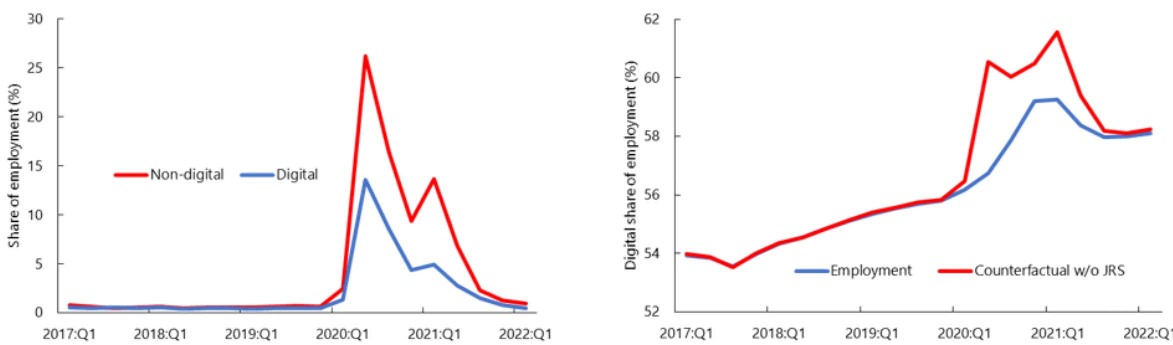
Coronavirus Job Retention Scheme (CJRS) for digital and non-digital occupations in Annex Figure 1.2. As in Cribb and others (2021) and Pizzinelli and Shibata (2023), in the Labour Force Survey, workers are classified as covered by the CJRS if they are employed but were away from work in the reference week either because their work was "interrupted by economic causes" or for "other" reasons. While this variable is a proxy, the constructed series tracks well the daily number of CJRS claimants reported by the Office of National Statistics. The analysis of work from home is based on a question regarding the usual location of work. Individuals who respond as working solely from home or in multiple locations but with their home as a base are classified as "working from home." The analysis of transitions into inactivity from employment uses the 2-quarter longitudinal version of the Labour Force Survey. The transition rate is computed as the ratio of workers moving from employment to inactivity across two quarters divided by the total employment level in the initial quarter, taking yearly averages. Values for 2022 are based on data up to Q3.

The second source, used in the region-level regressions of employment and vacancies shares of digital occupations, is the Annual Population Survey. Variables relating to demographic composition (share of prime-age workers, share of workers with a bachelor's degree, share of foreign-born population) and GDP per capita are downloaded at the NUTS-3 Region Level from the NOMIS online portal. The series on employment by occupation (using the three-digit UK SOC 2010 classification) are from ad hoc tabulations at the NUTS-3 level published by the Office of National Statistics upon request. These series are used to construct the level of employment in digital and non-digital occupations using crosswalks to convert the original digital scores from O*NET into the UK SOC2010 via a set of crosswalks (passing through the ISCO-08 classification).

Annex Figure 1.2. UK: Coronavirus Job Retention Scheme and Employment in Digital Occupations

1. Share of Employment Covered by the CJRS

2. Digital Share of Employment: Empirical and Counterfactual



Sources: Office of National Statistics Labour Force Survey and IMF staff calculations.
Note: Panel 1 shows the share of workers covered by the CJRS among those in digital (blue) and non-digital occupations. Panel 2 shows the historical share of workers employed in digital occupations (blue line) and a counterfactual based only on workers not protected by the CJRS (red line).

1.5 Vacancies Data

The data on vacancies used in the note are provided by Indeed, a large online job advertisement aggregator operating in numerous countries. Two types of data series are used. The regional analysis for the US and the UK uses micro data of individual job posts. The cross-country regressions use time series of vacancies for different standardized "categories" of jobs, called "norm-cats."

Individual-level vacancies data for the US and the UK

The analysis uses millions of positions posted on the platform from January 2019 until June 2022 containing the position's job title, the date the advertisement was first posted, and the location within the country. Even though a posting could be announcing multiple openings, previous works using Indeed data note that assuming one vacancy per posting replicates well the time-series variation of vacancies data from more traditional sources (Adrjan and others 2021).

A text-matching algorithm is used to assign an occupation from the four-digit version of the 2008 International Standard Classification of Occupations (ISCO-08) to each job title. Duval and others (2022) provides a more detailed description of the matching procedure. Through the four-digit ISCO-08 code, individual vacancies are then classified as digital or non-digital occupations through the O*NET digital score and the country-specific thresholds discussed in the main text.

The individual job postings are then aggregated to compute the total number of vacancies for digital and non-digital occupations for each region at monthly frequency. For the US, the location variable available in the Indeed data is at the county level. Counties are then aggregated to the Core-Based Statistical Area level, which includes both metropolitan and "micropolitan" areas. For the UK, the data contain their own classification of approximately 80 localities at a more aggregate level than NUTS-3 areas but representative of commuting zones and thus roughly comparable to Travel-to-Work Areas (e.g., large conurbations are grouped into "greater areas" such as the Greater London and Greater Manchester).

Normalized Categories

For a larger set of countries, the note uses vacancies data already aggregated by norm-cats—categories of postings standardized by Indeed based on both industry and occupation. These individual series are grouped into two series for digital and non-digital jobs. In the process, categories that are unclear in their nature are first dropped. Specifically, these are: "NA," "cat_uncategorized," "overall," "uncategorized," "tangible," "cat_community_and_social_service," and "military." The classification of the remaining norm-cats is displayed in Annex Table 1.2.

The sample countries in the Indeed vacancies data with norm-cats are AUS, AUT, BEL, CAN, CHE, DEU, ESP, FRA, IRL, ITA, JPN, LUX, NLD, NZL, and SWE.

Annex Table 1.2. Indeed NormCats

NormGroup	NormCat Name	Digital
Management	Management	√
	Project Management	√
Business and Finance	Accounting	√
	Banking & Finance	√
	Insurance	√
	Real Estate	√
	Marketing	√
	Human Resources	√
Healthcare	Personal Care & Home Health	
	Dental	
	Physicians & Surgeons	√
	Medical Information	√
	Nursing	√
	Medical Technician	√
	Pharmacy	√
	Therapy	
Education	Education & Instruction	√
Engineering	Architecture	√
	Chemical Engineering	√
	Civil Engineering	√
	Electrical Engineering	√
	Industrial Engineering	√
	Mechanical Engineering	√
Tech, Data, Science	Mathematics	√
	Scientific Research & Development	√
	IT Operations & Helpdesk	√
	Information Design & Documentation	√
	Software Development	√
Social Science, Law	Legal	√
	Social Science	√

NormGroup	NormCat Name	Digital
Food and Beverage	Food Preparation & Service	
Customer and personal service	Security & Public Safety	
	Customer Service	√
	Hospitality & Tourism	
	Beauty & Wellness	
Community	Childcare	
	Community & Social Service	
	Veterinary	
Arts, Culture, Sports	Arts & Entertainment	
	Media & Communications	√
	Sports	
Retail, and Sales	Retail	
	Sales	
Office and administrative support occupations	Administrative Assistance	√
Construction and extraction occupations (plus other reources)	Construction	
	Agriculture & Forestry	
	Mining	
Installation, maintenance, and repair occupations (plus	Installation & Maintenance	
sanitation)	Cleaning & Sanitation	
Production occupations	Production & Manufacturing	
Transportation and material moving occupations	Aviation	√
	Driving	
	Logistic Support	
	Loading & Stocking	

1.6 Google Mobility Index

The mobility indicators from Google's COVID-19 Community Mobility Reports are used in several regression analysis exercises to construct a measure of the COVID-19 shock to economic activity at a given regional level (e.g., country or subcountry level).[1]

In the context of the regional level regression analysis for the US, the following procedure is followed to construct the shock. First the average of the indicators for mobility in (1) retail and recreation areas and (2) transit locations is computed. Second, for each region the month with the most negative average daily value of the time series is selected (i.e., the month with the lowest average mobility). Finally, following the approach of

[1] https://www.google.com/covid19/mobility/

Chetty and others (2020), the shock is constructed as the drop in mobility for the selected month relative to the base period of January 2020.

In the context of the cross-country regression analysis of sector-level labor productivity, the following procedure is followed to construct the shock. First the average of the indicators for mobility in (1) retail and recreation areas and (2) transit locations is computed. For each country, an average yearly value of the composite index is computed. As the raw index represents the level relative to January 2020, the 2020 average reflects the mean change in mobility relative to the period shortly preceding the COVID-19 pandemic. For 2020, the change between the average of 2021 and the average of 2020 is constructed to represent the yearly change in mobility.

1.7 LinkedIn

Box 2 utilizes data provided by LinkedIn, a large online platform for professional networking and career development, operating in numerous countries. The data provided by LinkedIn consist of time series from 2017 to 2021 at the country-industry-occupation level for “technology skills penetration rate.” This is a metric developed by the LinkedIn Data Science team representing the share of technology-related skills among the new skills added by LinkedIn users to their profiles in a given year. To narrow the focus on recent developments, the metric only considers skills added by workers over the previous 12 months. Furthermore, a re-weighting algorithm is used to rank skills within an industry-occupation cell not only based on their frequency (i.e., how often they are added by workers) but by how distinctive they are (i.e., giving lower weight to skills that are also very common across industries and occupations).[3] The skill penetration rate is then computed as the share of the top 50 skills for industry-occupation cells that fall into the “technology” category, which is composed of an extensive list of “basic” and “disruptive” skills. The former group encompasses advanced and widely applicable skills in technology-related fields, such as different coding languages, software architecture, or ability to use specific ICT hardware. The disruptive group mostly covers abilities in fast-growing fields such as artificial intelligence. The skill penetration rate can thus be interpreted as a yearly “flow” measure of the degree to which technology skills are being updated within an industry and/or occupation.

Further data cleaning is carried out for the analysis presented in Box 2. The job titles in the raw LinkedIn data set are assigned standard ISCO-08 codes through a text-matching algorithm similar to that used for the Indeed vacancies data set (see Annex 1.6) followed by manual checks. Within each industry, simple averages are taken for job titles, which are assigned to the same three-digit ISCO-08 code to avoid duplication and over-representation of occupations that may have different job titles (e.g., job titles like Marketing Expert and Marketing Specialist are likely duplicating information). The ISCO-08 codes further allow for assigning to the job titles a respective O*NET digital score, which is used to produce Box Figure 2.1. For each country, the figure is computed by taking simple averages first for the same occupation across industries (e.g., if the same occupation appears in different industries with possibly different digital scores) and then across occupations within a given percentile range of the O*NET score.

Box Figure 2.2, focusing on the US only, computed the share of employment in digital occupations within each sector by weighing each industry-occupation cell by the average number of workers employed in that sector in the US in 2019. Employment levels across industries and occupations are downloaded from the Bureau of Labor Statistics website and converted into ISCO-08 occupations using a crosswalk.

Because of the characteristics of the sample and the way the skill penetration index is constructed, several qualifications are in order when interpreting the analysis of Box 2. First, the industrial and occupational composition of the LinkedIn pool of workers is unbalanced toward sectors and professions where digital intensity is relatively higher. Additionally, the analysis focuses on workers that voluntarily report skills in their profiles, potentially skewing the sample toward more tech-savvy individuals. Third, by concentrating on skills that are more distinctively characteristic of a job—meaning they are relatively less likely to be reported by workers in other jobs—the construction of the penetration score concentrates on relatively more advanced digital skills. This may prevent detecting instances of skill upgrading for occupations with relatively lower digital intensity since, presumably, workers in these jobs would initially add basic and widespread digital skills rather than advanced ones. Last but not least, using only skills that were added over the previous 12 months and focusing on the share of these skills that are technology-based, the penetration flow more closely represents a measure of the composition of the "flow" of updated skills.

1.8 Definition of Digital Occupations

The baseline categorization of digital occupations is based on the 6-digit SOC 2010 occupational classification for the US, and it is constructed starting from the methodology proposed by Muro and others (2017). The procedure, together with some descriptive analysis, is described in detail in Soh and others (2022). For each occupation code, a digital intensity score is constructed using two selected questions from the O*NET database. These questions measure the importance of knowledge of computers and the frequency of interaction with computers to carry out the main tasks defining an occupation. The values for each measure are combined to construct a single digital score for the occupation. Higher scores indicate higher digital intensity. Through a set of crosswalks, the score is also translated to the 4-digit ISCO-08 classification to be applied to the UK and other countries in the analysis. For each classification, the individual codes are ranked based on the digital score. In the baseline analysis, those with a score above the 50th percentile are considered to be digital and those with a score below this threshold are considered to be non-digital. For the US classification, a value of 53.2 corresponds to the 50th percentile. Soh and others (2022) provide examples of occupations at different percentiles of the distribution for the US.

For the cross-country data on digital employment presented in Figure 9 ISCO-08 1-digit occupation categories are used. These are nine occupation categories, once military occupations are excluded. Digital occupations are those whose average scores are above the 50th percentile of the distribution of the O*NET digital score based on aggregating more granular occupational groups for the US. These occupations are: i) managers (61.4), ii) professionals (64.0), iii) technicians and associate professionals (59.5), and iv) clerical support workers (56.3). The values in the parentheses are the digital scores based on O*NET digitalization measures.

Annex 2. Digital Intensity Decomposition

Methodology for decomposing digital intensity data

The decomposition charts (Annex Figure 2.1) are created following the three steps below:

Step 1 – Estimate the average level of digitalization in the sample $\bar{d}$

$$\bar{d} = (\sum\sum \omega_{ij} d_{ij})/\bar{n}$$

where i indicates the sector and j the country, ω_{ij} is the sectoral employment share in a country j and sector i, and $\bar{n}$ represents the number of countries in our sample.

Step 2 - To decompose the difference between country j digitalization and average digitalization in the sample $\bar{d}$, the difference is rewritten as:

$$d_j - \bar{d} = \sum_i \omega_{ij} d_{ij} - \frac{\sum\sum \omega_{ij} d_{ij}}{\bar{n}} =$$

$$= \sum_i \omega_{ij} d_{ij} - \sum_i \omega_{ij} \sum_j \frac{d_{ij}}{\bar{n}} + \sum_i \omega_{ij} \sum_j \frac{d_{ij}}{\bar{n}} - \frac{\sum\sum \omega_{ij} d_{ij}}{\bar{n}}$$

The first term $(\sum_i \omega_{ij} d_{ij} - \sum_i \omega_{ij} \sum_j \frac{d_{ij}}{\bar{n}})$ captures gap in digitization that is driven by differences in digitalization within sectors. The second term $(\sum_i \omega_{ij} \sum_j \frac{d_{ij}}{\bar{n}} - \frac{\sum\sum \omega_{ij} d_{ij}}{\bar{n}})$ captures the importance of the sectoral differences in explaining the digitalization gap. Annex Figure 2.1, panel 1, is then created accordingly.

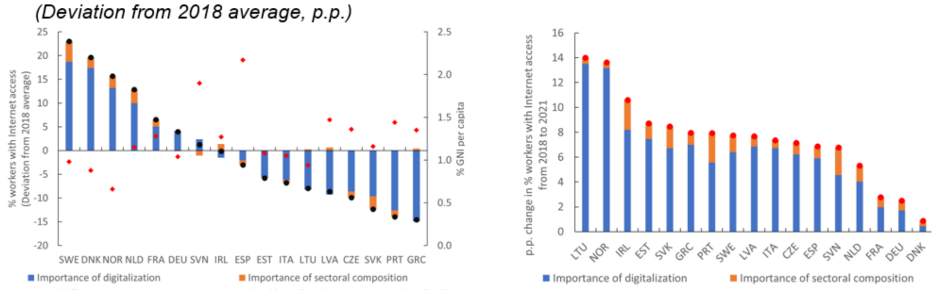
Step 3 – Annex Figure 2.1, panel 2 is based on the decomposition of growth rate of digitalization in country i and sector j

$d_{it} - d_{it-1} = \sum_j \omega_{jt} d_{jt} - \sum_j \omega_{jt-1} d_{jt-1} = \sum_j \omega_{jt} d_{jt} - \sum_j \omega_{jt} d_{jt-1} + \sum_j \omega_{jt} d_{jt-1} - \sum_j \omega_{jt-1} d_{jt-1}$The first term $(\sum_j \omega_{jt} d_{jt} - \sum_j \omega_{jt} d_{jt-1})$ captures sectoral differences in digitalization, while the second term ($\sum_j \omega_{jt} d_{jt-1} - \sum_j \omega_{jt-1} d_{jt-1}$) captures sectoral differences in composition.

Annex Figure 2.1. Digital Intensity Decomposition

1. Decomposition of Cross-Country Differences in Digitalization into Differences across Sectors and Sector Shares
(Deviation from 2018 average, p.p.)

2. Decomposition of Change in Digitalization
(Percentage point change in digitalization from 2018 to 2021)



Sources: Eurostat and IMF staff calculations.
Note: Panel 1 and 2, based on the balanced panel that includes countries having non-missing sectoral employment and digitalization measure (hence BEL, FIN and LUX are not included), show the digitalization decomposition into the importance of sectoral digitalization and sectoral composition. Details on the decomposition methodology can be found in Annex 2.

Annex 3. Productivity Regression Analysis

3.1 Cross-country sector-level analysis

The regression analysis presented in Section III is conducted through the following specification:

$$\Delta\%\, y_t^{ic} = \alpha + \boldsymbol{\beta}\, \boldsymbol{X}^i + \gamma\, Digital_t^{ic} + \ \delta\, Mobility_t^c + \eta \left(Mobility_t^c * \ Digital_t^{ic} \right) + \kappa\, JRS_{2020}^c + \lambda \left(Mobility_t^c * \ RS_{2020}^c \right) + \ \theta_i + \ \epsilon_t^{ic}$$

The dependent variable $\Delta\%\, y_t^{ic}$ is the yearly growth rate of labor productivity in sector *i* of country *c* at time *t* = 2020, 2021. This is regressed on a constant, and time invariant controls for country-level demographic characteristics $\boldsymbol{X}^i$, the contemporaneous share of workers using an internet-connected computer $Digital_t^{ic}$, a the country-level mobility indicator $Mobility_t^c$, an interaction between digital intensity and mobility, the share of workers covered by a job retention scheme in May 2020 JRS_{2020}^c, an interaction between this variable and mobility, and a sector fixed effect θ_i. The mobility indicator is constructed using the Google Mobility Index, as described in Annex 1.6. The vector $\boldsymbol{X}^i$ includes country-level demographic characteristics from 2018: the share of prime-age workers, the share of young workers, the share of workers with a bachelor's degree, and real GDP per capita in 2018. The share of workers covered by a job retention scheme in May 2020, which is taken from the OECD 2022 Employment Outlook, and its interaction with the mobility index are meant to control for the extent of governmental response to protect jobs, which may have affected productivity by retaining employment. Moreover, this effect may have varied depending on the severity of the economic shock. Standard errors are clustered at the country-year level.

The coefficients of interest are those of the mobility index and the interaction term with digital intensity, which can be used to derive the differential growth of productivity in a given year associated with having a higher level of digital intensity prior to the pandemic. Note that the regression contains contemporaneous digital intensity levels, possibly leading to reverse causality: productivity growth in an early year may be the cause of higher digital intensity in the same year. Results are robust to using the lag of digital intensity or the 2019 value for both 2020 and 2021. Annex Table 3.1 reports the estimated coefficient and *R*-squared.

Sensitivity analysis shows that comparable results emerge if the same regression specification is estimated using the share of firms purchasing cloud computing services as a measure of digital intensities from Eurostat described in Annex 1 (Annex Figure 3.1).

The alternative specification adding a control for contact intensity, used to produce Figure 5, panel 2, is as follows:

$$\Delta\%\, y_t^{ic} = \alpha + \boldsymbol{\beta}\, \boldsymbol{X}^i + \gamma\, Digital_t^{ic} + \ \delta\, Mobility_t^c + \zeta\, ContactInt^i + \ \eta^C \left(Mobility_t^c * \ Digital_t^{ic} * (ContactInt^i = 1) \right) + \ \eta^{NC} \left(Mobility_t^c * \ Digital_t^{ic} * (ContactInt^i = 0) \right) + \kappa\, JRS_{2020}^c + \lambda \left(Mobility_t^c * \ RS_{2020}^c \right) + \ \theta_i + \ \epsilon_t^{ic}$$

Where $ContactInt^i$ is a dummy variable equal to 1 for the following sectors: food and accommodation, construction, transport and storage, wholesale and retail trade.

Linear combinations of the coefficients are used, together with descriptive statistics of the distribution of digital intensity, to compute the predicted changes in productivity displayed in Figure 4 of the main text. The yearly growth rates in Figure 5, panel 1, are computed by multiplying the coefficients of interest with some chosen values for the variables they correspond to and then summing over them. Specifically, the three bars for 2020 are computed as $\delta\, \overline{Mobility_{2020}} + \eta\, (\overline{Mobility_{2020}} * Digital_{2020})$, where $\overline{Mobility_{2020}}$ is the average cross-country mobility fall in 2020 and $Digital_{2020}$ is one of three counterfactual values. The first value (green bars) represents the mean of digital intensity in 2020 across all countries and sectors. The other values are the 25th and 75th percentiles of the distribution of sector-adjusted digital intensity. These are computed by first subtracting from each country-sector observation the average digital intensity of the sector and then adding the average intensity computed across all sectors. Hence, the percentiles capture only within-sector dispersion in digital intensity for the "average" sector and abstract from variation originating from average difference between sectors. The bars for 2021 follow the same procedure but using values specific to 2021.

Annex Table 3.1. Country-Sector-Level of Labor Productivity Growth (percent) for Advanced European Economies.

Baseline

Dependent Variable: Yearly Growth Rate of Labor Productivity	**Coefficient**	**Robust Standard Error**	**p-Value**
Mobility	0.481	0.130	0.00
Digital	-0.088	0.062	0.17
Mobility X Digital	-0.004	0.001	0.01
JRS	-0.125	0.050	0.02
Mobility X JRS	-0.009	0.003	0.00
Log GDP per capita	-0.388	3.258	0.91
Share Prime Age	0.028	0.064	0.67
Share Bachelor's	-0.063	0.082	0.45
Share Young	0.602	0.668	0.37
Observations	358		
R-squared	0.186		
Sector FE	YES		

Interaction with contact-intensity

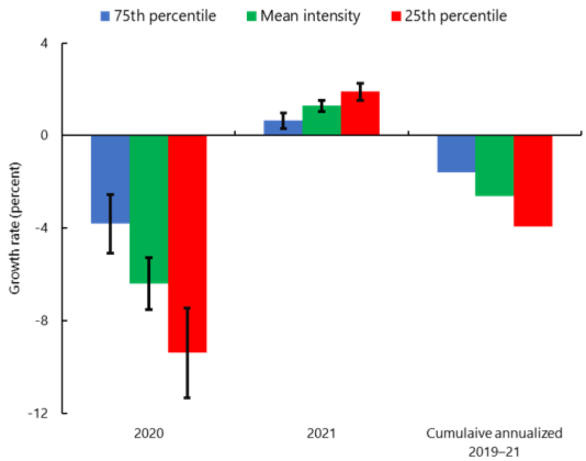
Dependent Variable: Yearly Growth Rate of Labor Productivity	**Coefficient**	**Robust Standard Error**	**p-Value**
Mobility	0.340	0.136	0.02
Digital	-0.066	0.061	0.29
Contact-Intensive	5.740	1.900	0.00
Mobility X Digital X (Contact-Intensive=0)	-0.0027	0.001	0.052
Mobility X Digital X (Contact-Intensive=1)	0.0001	0.002	0.955
JRS	-0.120	0.050	0.02
Mobility X JRS	-0.009	0.003	0.00
Log GDP per capita	-0.512	3.260	0.88
Share Prime Age	0.024	0.064	0.70
Share Bachelor's	-0.051	0.082	0.54
Share Young	0.611	0.677	0.37
Observations	358		
R-squared	0.223		
Sector FE	YES		

Sources: Eurostat; OECD; UK Office of National Statistics; and IMF staff calculations.
Note: Standard errors are clustered at the country-year level.

The counterfactual exercises discussed in Section III.1 are also based on linear combinations of the coefficients, using the specification that is augmented with contact intensity. For each country-sector-year observation, the "predicted" change in productivity in 2020 is constructed as:

$$\Delta\%\, \widehat{y^{ic}_{2020}} = \delta * Mobility^{c}_{2020} + \eta^{C}\left(Mobility^{c}_{2020} * Digital^{ic}_{2020} * (ContactInt^{i} = 1)\right) + \eta^{NC}\left(Mobility^{c}_{2020} * Digital^{ic}_{2020} * (ContactInt^{i} = 0)\right) + \kappa\, JRS^{c}_{2020} + \lambda\,(Mobility^{c}_{t} * RS^{c}_{2020})$$

Annex Figure 3.1. Regression Result on Labor Productivity Using the Share of Firms Purchasing Cloud Services to Measure of Digitalization



Sources: Eurostat; Organisation for Economic Cooperation and Development; and IMF staff calculations.
Note: The Figure plots a linear combination of the estimated regression coefficients representing the predicted labor productivity growth rate, in a country experiencing an average change in mobility, for a sector with high (90th percentile), average, or low (10th percentile) digital intensity based on a sector-adjusted distribution (i.e., abstracting from between sector average levels of digitalization). The measure of digital intensity used is the share of firms purchasing cloud services, which is available for a small sample of country-sector observations. Country sample: AUT, BEL, CZE, DEU, DNK, ESP, EST, FIN, FRA, GBR, GRC, IRL, ITA, LTU, LUX, LVA, NLD, NOR, PRT, SVK, SVN, SWE. Annex 2 describes the regression specification and the data in detail.

where $Digital^{ic}_{2020}$ is the empirical level of digitalization in 2020 for sector i in country *c*. A counterfactual prediction is then constructed as:

$$\Delta\%\ \widehat{y^{ic}_{2020}}^{75th} = \delta * Mobility^{c}_{2020} + \eta^{C}\left(Mobility^{c}_{2020} * Digital^{i\,75th}_{2020} * (ContactInt^{i} = 1)\right) + \eta^{NC}\left(Mobility^{c}_{2020} * Digital^{i\,75th}_{2020} * (ContactInt^{i} = 0)\right) + \kappa\, JRS^{c}_{2020} + \lambda\,(Mobility^{c}_{t} * RS^{c}_{2020})$$

where $Digital^{i\,75th}_{2020}$ is the 75th percentile of digitalization in sector *i*. Based on $\Delta\%\ \widehat{y^{ic}_{2020}}$ and $\Delta\%\ \widehat{y^{ic}_{2020}}^{75th}$ and on empirical productivity values for 2019, the counterfactual sector-level productivities $\widehat{y^{ic}_{2020}}$ and $\widehat{y^{ic}_{2020}}^{75th}$ are created and, using hours worked, are aggregated to compute country-level productivity counterfactuals. From these, counterfactual country-level growth rates of productivity are then computed $\Delta\%\ \widehat{y^{c}_{2020}}$ and $\Delta\%\ \widehat{y^{c}_{2020}}^{75th}$ using the empirical 2019 productivity value as a baseline. Finally, for countries with below the median aggregate digital intensity, the difference between the predicted growth rate and the counterfactual prediction using the 75th percentile is computed. The 2019 median country-level share of workers using computers with internet access, weighting the sectors in the samples by hours worked in 2019, is approximately 57 percent. The country sample with below-the-median digital intensity is: LUX, GRC, PRT, SVK, LVA, SVN, CZE, EST, LTU, ITA, ESP.

3.2 Firm-level analysis

To study how digitalization impacted firm productivity during the pandemic, a cross-country firm-level data set (Worldscope) is employed. The framework presented in Section III.2 closely follows Duval and others (2020). Specifically, the average within-firm TFP growth between the pre- and post-pandemic periods is calculated and regressed on ex ante digitalization measures, firm-level controls, and sector and country/state fixed effects. The regressions are run separately for 2020 and 2021, and they are run separately for the US and European samples as the digitalization measures differ: for the US the measure employed is at the firm level and defined as the log of computer equipment and software over workers, whereas for Europe the measure employed is at the country-sector level and defined as the share of workers with Internet access. The empirical specifications are presented below.

Advanced Europe

The baseline regression, which is run for 2021 and 2020 separately, follows closely

$$(\Delta TFP_{i,c,s,t}^{t} - \Delta TFP_{i,c,s,pre}^{avg}) = \beta\ ICT_{s,c}^{pre} + \alpha_s + \gamma_c + \delta' X_i + \epsilon_{i,s,c,t},$$

where $\Delta TFP_{i,c,s,t}^{t}$ is the annual change is log TFP for t=2021 and t=2020 respectively and $\Delta TFP_{i,c,s,pre}^{avg}$ is the pre-pandemic average annual change in log TFP defined as:

$$\Delta TFP_{i,c,s,pre}^{avg} = 0.5(logTFP_{i,c,s,2019} - logTFP_{i,c,s,2018}) + 0.5(logTFP_{i,c,s,2018} - logTFP_{i,c,s,2017}).$$

The dependent variable of the regression captures the within-firm difference in TFP growth of firm i in sector s and country c between the post-pandemic period (2020 and 2021, respectively) and its pre-pandemic average. $ICT_{c,s}^{pre}$ denotes the 2017–19 average of ICT intensity at the country-sector level (i.e., the share of workers with internet access), and X_i is a vector of firm-level controls, including the age of the firm, its pre-pandemic size (measured as the log of its total assets), and pre-pandemic profitability (measured as earnings over total assets). The terms α_s and γ_c denote the country and sector fixed effects. Standard errors are clustered at the country-sector level. The key parameter of interest is β, which captures the effect of pre-pandemic ICT intensity on within-firm change in TFP growth in the pre- and post-pandemic period. The results are presented in Annex Table 3.2:

Annex Table 3.2. Firm-Level Regression on TFP Growth Rate Differences (in percentage points) for Advanced European Economies

Dependent variable: Difference in the TFP growth rate between pre-pandemic average and t	t=2020	t=2021
Pre-pandemic avg share of workers with internet access	-0.0293	0.2027***
	(.083)	0.06065
Observations	1,580	1,580
R-squared	0.1985	0.1133
Sector FE	YES	YES
Country FE	YES	YES
Root mean square error	8.8951	9.3949

Sources: Worldscope; Organisation for Economic Co-operation and Development; and IMF staff calculations.
Note: Standard errors are clustered at the country-sector level. *** p<0.01, ** p<0.05, * p<0.1

United States

A similar specification is employed for the US sample:

$$(\Delta TFP_{i,s,t}^{t} - \Delta TFP_{i,s,pre}^{avg}) = \beta\, ICT_{i}^{pre} + \alpha_{s,st} + \gamma' X_i + \epsilon_{i,s,t},$$

where $\Delta TFP_{i,s,t}^{t}$ is the annual change is log TFP for t=2021 and t=2020 respectively and $\Delta TFP_{i,s,pre}^{avg}$ is the pre-pandemic average annual change in log TFP defined as:

$$\Delta TFP_{i,c,s,pre}^{avg} = 0.5(logTFP_{i,c,s,2019} - logTFP_{i,c,s,2018}) + 0.5(logTFP_{i,c,s,2018} - logTFP_{i,c,s,2017}).$$

ICT_{i}^{pre} denotes the 2017–19 average of ICT intensity at the firm level (i.e., the log of the share of computer equipment and software over workers), and X_i is a vector of firm-level controls including the age of the firm, its pre-pandemic size (measured as the log of its total assets), and pre-pandemic profitability (measured as earnings over total assets). The term $\alpha_{s,s}$ denotes the state-sector fixed effects. Standard errors are clustered at the state-sector level. The key parameter of interest is β, which captures the effect of pre-pandemic ICT intensity on within-firm change in TFP growth in the pre- and post-pandemic period. The results are presented in Table 3.3:

Annex Table 3.3. Firm-Level Regression on TFP Growth Rate Differences (in percentage points) for US

Dependent variable: Difference in the TFP growth rate between pre-pandemic average and t	t=2020	t=2021
Pre-pandemic avg ICT intensity	0.00073	0.018***
	(0.0083)	(0.017)
Observations	440	440
R-squared	0.5587	0.5778
State*Sector FE	YES	YES
Root mean square error	0.08903	0.08284

Sources: Worldscope; Organisation for Economic Co-operation and Development; and IMF staff calculations.

Note: Standard errors are clustered at the state-sector level. *** p<0.01, ** p<0.05, * p<0.1

Historical link between total factor productivity and digitalization

To study how digitalization has historically impacted firm-level total factor productivity, the unbalanced US Worldscope data set is employed. The analysis focuses on the decade preceding the pandemic crisis (2011–19) and builds on the empirical framework of Borowiecki and others (2021). Firms are first divided into frontier and non-frontier firms by year and sector (frontier firms being those at the top 5% of the TFP distribution), and the following regression is estimated for the TFP growth of non-frontier firms:

$$\Delta TFP_{i,s,t} = \alpha \Delta TFP_{i,s,t} + \beta gap_{i,s,t-1} + \gamma\, ICT_{i,s,t-1} + \delta' \mathrm{X}_{i,s,t} + \alpha_s + \zeta_t + \epsilon_{i,s,t}$$

where $\Delta TFP_{i,s,t}$ is the annual change of log TFP for the non-frontier firm *i* in sector s, $\Delta TFP_{frontier,s,t}$ is the annual change of log TFP for the frontier firms, and $gap_{i,s,t-1}$ is the lagged distance between the TFP of frontier and remaining firms for each sector-year cell. Based on economic theory, coefficients α and β are expected to be positive, capturing the positive impact of technology diffusion from frontier firm innovation and catch-up of laggard firms. Controls for firm-level characteristics denoted by $\mathrm{X}_{i,s,t}$ (such as firm age, size, and profitability) are added, as well as sector and time fixed effects to capture differences across sectors and aggregate time trends. Finally, $ICT_{i,s,t-1}$, is the lagged digitalization measure at the firm level, defined as the log of computer equipment and software over workers. The same regression with labor productivity growth as the dependent variable is also estimated. The results are presented in Annex Table 3.4:

Annex Table 3.4. Firm-Level Regression on TFP Growth Rate for US

Dependent variable:	TFP growth rate	LP growth rate
Frontier firm' TFP growth	0.1480***	0.0815*
	(0.033)	(0.0410)
Lagged productivity gap	0.052***	0.0494***
	(0.004)	(0.0102)
Lagged Computer & Software/Workers (log)	0.003***	0.00529***
	(0.001)	(0.00104)
Total Assets (log)	0.00171***	0.00278*
	(0.0004)	(0.00130)
Age	-0.202*	-0.00685***
	(0.0006)	(0.0005)
Observations	6,799	7,084
R-squared	0.08	0.0891
Sector FE	YES	YES
Year FE	YES	YES
Root mean square error	0.0879	0.1662

Sources: Worldscope; Organisation for Economic Co-operation and Development; and IMF staff calculations.
Note: Standard errors are clustered at the state-sector level. *** p<0.01, ** p<0.05, * p<0.1

Annex 4. Employment Regression Analysis

4.1 Cross-Country Cross-Sector Analysis

The regression analysis of hours worked at the country and sector levels in Section IV.1 follows the specification of the productivity growth regression described in Annex 2.1, using the growth rate of hours worked as the dependent variable. Annex Table 4.1 reports the estimation results.

Annex Table 4.1. Country-Sector-Level of Hours Worked Growth (percent) for Advanced European Economies.

Baseline

Dependent Variable: Yearly Growth Rate of Hours Worked	Coefficient	Robust Standard Error	p-Value
Mobility	0.876	0.059	0.00
Digital	-0.068	0.041	0.11
Mobility X Digital	-0.009	0.001	0.00
JRS	0.080	0.027	0.01
Mobility X JRS	0.005	0.001	0.00
Log GDP per capita	0.042	1.729	0.98
Share Prime Age	0.032	0.071	0.66
Share Bachelor's	0.054	0.044	0.23
Share Young	0.357	0.311	0.26
Observations	358		
R-squared	0.828		
Sector FE	YES		

Interaction with contact-intensity

Dependent Variable: Yearly Growth Rate of Hours Worked	Coefficient	Robust Standard Error	p-Value
Mobility	0.846	0.068	0.00
Digital	-0.063	0.042	0.14
Contact-Intensive	0.106	1.067	0.92
Mobility X Digital X (Contact-Intensive=0)	-0.0084	0.0007	0.0000
Mobility X Digital X (Contact-Intensive=1)	-0.0078	0.0011	0.0000
JRS	0.081	0.027	0.00
Mobility X JRS	0.005	0.001	0.00
Log GDP per capita	0.015	1.745	0.99
Share Prime Age	0.031	0.069	0.66
Share Bachelor's	0.056	0.044	0.21
Share Young	0.359	0.307	0.25
Observations	358		
R-squared	0.223		
Sector FE	YES		

Sources: Eurostat; OECD; UK Office of National Statistics; and IMF staff calculations.
Note: Standard errors are clustered at the country-year level.

4.2 US Region-Level Analysis

Region-level analysis for the US follows the sample selection and specification of Soh and others (2022). The dependent variable is the change in the difference in the log of either digital or non-digital employment in each quarter *t* from 2020:Q1 to 2022:Q2 relative to the respective quarter in 2019 within a state m $(Y_{m\,t} - Y_{m\,2019})$.

To understand the impact of exposure to the COVID-19 shock on the change in employment in each region, the following specification is estimated:

$$Y_{m\,t} - Y_{m\,2019} = \alpha_0 + \boldsymbol{\beta}'\boldsymbol{X_m} + \gamma\, shock_m + \sum_k \big(\delta_k\, I(t = k) + \eta_k\, shock_m\, I(t = k)\big) + \epsilon_{mt}$$

where $Y_{m\,t} - Y_{m\,2019}$ is the change in employment (either digital or non-digital) between period t and corresponding quarter in 2019 in state m, $shock_m$ is a Bartik-type shock, $\boldsymbol{X_m}$ is a sector of time-invariant state-level demographic controls such as the share of prime-age workers, workers with a bachelor's degree, the share of foreign workers, and GDP per capita (computed as averages from 2017–18). The coefficients of interest are those related to the interaction between $shock_m$ and the time dummies η_k. These capture the differential effect on the growth of employment in digital occupations associated with greater exposure to the impact of COVID-19.

Following Hershbein and Kahn (2018), the Bartik shock is constructed as follows:

$$shock_m = \Delta\,\widehat{E}_{m\,2020Q2} - \Delta\widehat{E}_{m\,2019Q2}$$

where

$$\Delta\,\widehat{E}_{m\,2020Q2} = \sum_{j=1}^{J} \omega_{m,j\;2017-2018}\,(\ln E_{j,2020Q2} - \ln E_{j,2019Q2})$$

$$\Delta\widehat{E}_{m\,2019Q2} = \sum_{j=1}^{J} \omega_{m,j2017-2018}\,(\ln E_{j,2019Q2} - \ln E_{j,2018Q2})$$

where the subscript j stands for the two-digit NAICS industry, $\omega_{m,j2017-2018}$ is the employment share in state m of that industry in 2017–18, and $\ln E_{j,t}$ is the natural log of the national employment level in industry j and period t. The Bartik shock serves as a proxy of the drop in employment growth at the trough of the pandemic in a given state that can likely be explained by its industrial composition prior to the pandemic and national employment dynamics. It can therefore be interpreted as a measure of the exposure of each state to the aggregate shock to employment.

4.3 UK Region-Level Analysis

Region-level analysis for the UK follows a similar specification as for the US with a few key differences. First, as employment information from the Annual Population Survey is only available as yearly averages, the dependent variable is the change in the log employment of digital or non-digital occupations in year *t* relative to 2019, where *t* is 2020 or 2021. Second, in the UK, thanks to the wide reach of the government's Coronavirus Job Retention Scheme, the employment contraction during COVID-19 was markedly milder than in the US and with substantially smaller differences across sectors. Hence, the Bartik shock does not serve well as a measure of region's ex ante exposure to the COVID-19 shock. The percent drop in the Google Mobility Index during April–December 2020 relative to January 2020 is used as an alternative (see Annex 1.6 for details).

Even though employment information from the Annual Population Survey is available at the NUTS-3 region level, the geographic unit of observation is based on the Indeed regional classification for comparability with the regression analysis for vacancies.

Annex 5. Vacancies Regression Analysis

5.1 Cross-Country Analysis

To understand the impact of COVID-19 shocks on the differential cumulative growth of digital vacancies, a series of regressions for different periods are run with the following specification:

$$lny_{jct} - lny_{jct_{(2019,q)}} = \alpha_0 + \alpha_1 shock_c + \gamma_t\left(shock_c \times Digital_j\right) + \delta' X_c + \epsilon_{jct}$$

where $lny_{jct} - lny_{jct_{(2019,q)}}$ is the cumulative growth of vacancies between quarter t and corresponding quarter in 2019, $t_{(2019,q)}$ in country *c*. $shock_c$ is either the Bartik shock (baseline) or the Google Mobility shock. The vector of controls X_c includes the share of population with bachelor's degree, the share of prime-age workers, real GDP per capita, the fraction of digital vacancies in 2018, and the COVID-19 stringency index by country to account for policy response differences—produced by the University of Oxford's COVID-19 Government Response Tracker.

Following Hershbein and Kahn (2018), we calculate the Bartik shock as follows:

$$shock_c = \Delta E_{c2020} - \Delta E_{c2019}$$

where

$$\Delta E_{c2020} = \sum_{j=1}^{J} \omega_{c,j2017-2018}\left(\ln E_{j,2020} - \ln E_{j,2019}\right)$$

$$\Delta E_{c2019} = \sum_{j=1}^{J} \omega_{c,j2017-2018}\left(\ln E_{j,2019} - \ln E_{j,2018}\right)$$

where $\ln E_{j,y} - \ln E_{j,y-1}$ is log difference of aggregate industry employment between year *y* and *y-1* and $\omega_{c,j2017-2018}$ is the average employment share of industry *j* in country *c* between 2017 and 2018.

Figure 10, panel 3, in the main text, plots the coefficients on the interaction of *shock* and *Digital* norm-cat dummies, γ_t for each quarter between 2020:Q1 and 2022:Q2. Due to the availability of shocks and comparison with different analysis in this Staff Discussion Note, the following countries are included in the sample: AUS, AUT, BEL, CAN, CHE, DEU, ESP, FRA, GBR, IRL, ITA, JPN, LUX, NLD, SWE, and USA.

5.2 US and UK Region-Level Analysis

Region-level regression analysis for the US and the UK is conducted using the same specification as for the employment regressions. See Annex 3 and Soh and others (2022) for a more detailed discussion. The dependent variable is the change in the share of vacancies in digital occupations between a given quarter and the respective quarter of the year in 2019 (e.g., 2021:Q4 relative to 2019:Q4).

For the US the regressions are run at the core-based statistical area (CBSA) level, as vacancies data from Indeed contain the county in which each job advertisement was posted. For the UK, the regressions are run at a granular regional level containing approximately 70 localities. See Annex 1.6 for details on the location variables present in the Indeed data set.

Annex 6. Working from Home

6.1 Model

To gauge the potential long-term impact that working from home can have on labor supply, this annex develops a household model of labor supply that incorporates the time saved from commuting to work that working from home often provides. Households differ on each spouse's ability to work from home, which depends on their occupation, $i, j \in \{r, c\}$, four types of households are simulated. Households maximize joint utility by choosing husband's c_i^m and wife's c_j^f consumption and husband l_i^m and wife leisure l_j^f :

$$\max_{c_i^m c_j^f, l_i^m, l_j^f} \quad \log c_i^m + \log c_j^f - \phi_i^m \frac{(l_i^m + T_i^m)^{1+\gamma}}{1+\gamma} - {\phi_j}^f \frac{\left(l_j^f + T_j^f\right)^{1+\gamma}}{1+\gamma}$$

such that

$$c_i^m + c_j^f \leq l_i^m w_i^m + l_j^f w_j^f$$

$$c_i^m, c_j^f, l_i^m, l_j^f \geq 0, l_i^m, l_j^f \leq 1, \quad i, j \in \{r, c\}$$

where T_i^f and T_j^m are the commuting time in each occupation. Husband's and wife's labor supply can be characterized when the solution is interior

$$\phi_i^m (T_i^m + l_i^m)^\gamma \;=\; \frac{2\, w_i^m}{(w_i^m\, l_i^m + w_j^f\, l_j^f)}$$

$$\phi_j^f \left(T_j^f + l_j^f\right)^\gamma \;=\; \frac{2\, w_j^f}{(w_j^m l_j^m + w_i^f\, l_i^f)}$$

From the equations above, it is possible to verify that a decline in the agent's commuting time leads to an increase in the agent's hours worked and a decline in the spouse's hours worked, while an increase in the preference for leisure leads to a decline in the agent's hours worked and increase in the spouse's hours worked.

6.2 Data

The model is calibrated using data from the American Time Use Survey (ATUS), which allows computing the time spent at home and commuting at the micro level. The data are detrended to control for long-term trends in hours worked, like the decline in men's working hours and the increase in women's working hours over time. The model considers four types of households, depending on the teleworkability of each individual. Annex Table 6.1 summarizes the amount of time spent on each activity before and after the pandemic.

Annex Table 6.1. Hours Spent Working and Commuting

		Before the Pandemic		After the Pandemic		Working Diff.	Commuting Diff.
		Working	Commuting	Working	Commuting		
Women	Tele	35.5	2.8	35.7	1.8	0.2	-1.0
	Non-tele	30.6	2.4	30.6	2.4	0.1	0.1
Men	Tele	43.2	4.1	41.3	2.1	-1.9	-2.1
	Non-tele	42.4	3.9	43.3	3.7	0.9	-0.2

Sources: ATUS; and IMF staff calculations.

Note: Working and commuting before the pandemic consist of the average time spent on these activities between 2016 and 2019, and after the pandemic refers to 2021 numbers.

The model has 13 parameters. Nine are chosen exogenously, while four are calibrated endogenously. We start by describing the exogenous parameters. First, we choose the Frisch elasticity of labor supply to be equal to 3, a standard value used in the literature. Second, the average men's and women's commuting time are chosen, from the ATUS, to match the average time each spouse spent commuting before the pandemic, as described in Table 6.1. The wage for each occupation is chosen to match the wage premium between men and women in teleworkable and non-teleworkable occupations from the Current Population Survey 2019 (CPS). The last four parameters, husband's and wife's disutility of work, which depends on their occupation, are calibrated endogenously to match the average hours worked in each occupation by gender before the pandemic, as described in Annex Table 6.1.

6.3 Shocks

Two pandemic-induced shocks are considered. The first is a commuting time shock that replicates the reduction in commuting time observed across teleworkable occupations in the data and shown in Annex Table 6.1. The second is a leisure shock replicating the changes in hours worked experienced by men in non-teleworkable occupations after the pandemic. This shock is applied to men working in both teleworkable and non-teleworkable occupations.

Annex 7. Box A1

Box A1. Next Generation EU Funds[1]

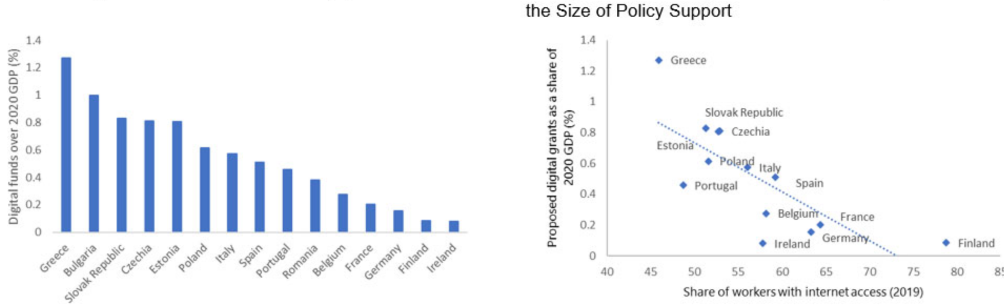
The Next Generation EU (NGEU) constitutes an important example of policy support in response to the economic and structural challenges triggered by the COVID-19 shock, and a key case study of policy measures that directly target the need for digital transformation, which the pandemic intensified. The NGEU is an EU-wide program that provides funding to EU member states subject to the implementation of reforms and investment plans aligned with EU guidance over the period 2021–26, with the aim of accelerating the recovery of member states and boosting their resilience, convergence, and modernization. The majority of NGEU funds will be disbursed under the RRF (Recovery and Resilience Facility), which accounts for approximately 90 percent of the program. This box provides an overview of the RRF, with a particular focus on proposed RRF grants earmarked for digital transformation investments.

Analysis using EU country survey data based on country proposals for RRF digital funds from 15 EU countries suggests considerable policy support targeted at the development and absorption of digital technologies and processes. Specifically, the size of support ranges from approximately 1.3 percent of 2020 GDP (for the case of Greece) to 0.08 percent of 2020 GDP (for the case of Ireland; Box Figure A1, panel 1). The RRF supported reforms, and investments are targeted toward a broad range of digitalization measures that cover both the public and the private sectors. Examples of investment projects proposed under the National Recovery and Resilience Plans that are targeted to the public sector include the enhancement of e-government and the digitalization of administration processes, the improvement of digital infrastructure for schools, an increase in cybersecurity and cloud and data processing, and enhancement of digital infrastructure that will improve reliability of the digital business environment. Measures targeted to the private sector include funding support to firms for the development of digital technologies and digital-related R&D (such as artificial intelligence, automation, and blockchain) and support for the absorption of digital products, services, and processes, with a strong focus on SMEs.

Box Figure A1. EUR Survey Data on the Proposed Digital Grant Allocations

1: Share of Digital Grants over 2020 GDP (%)

2: Negative Relationship between Ex-ante Digitalization and the Size of Policy Support



Source: EUR and IMF staff calculations.
Note: Countries included: BEL, CZE, DEU, ESP, EST, FIN, FRA, GRC, IRL, ITA, POL, PRT, SVK. The proposed Digital Funds are based on most recent EUR country survey data on proposed Recovery and Resilience Plans.

Countries that were less digitalized prior to the pandemic have the most ambitious digital transformation grant allocation proposals, suggesting increased efforts for digital catch-up. In line with the NGEU's aim, which is to enhance the resilience and innovative potential of member countries and provide critical support to lagging countries, there is a negative relationship between size of RRF digital funds over GDP proposals and the share of workers with internet access prior to the pandemic (Box Figure A1, panel 2), pointing to learning from governments on the positive effects of digitalization. Catalyzing NGEU funding is critically tied to implementation of broad-ranging reforms that aim to upgrade national capacity (covering labor and product market reforms, as well as reforms on the pension system, social inclusion, climate policy and energy transition, education, and health care). Leveraging both the large policy support and needed reforms will be key for addressing structural challenges that emerged during the pandemic and for paving the way to convergence and accelerated economic development.

[1] Prepared by Myrto Oikonomou.

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