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Digitalization and Resilience

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Abstract

This paper investigates the role of digitialization in improving economic resilience. Using balance sheet data from 24,000 firms in 75 countries, and a difference-in-differences approach, we find that firms in industries that are more digitalized experience lower revenue losses following recessions. Early data since the outbreak of the COVID-19 pandemic suggest an even larger effect during the resulting recessions. These results are robust across a wide range of digitalization measures—such as ICT input and employment shares, robot usage, online sales, intangible assets and digital skills listed on online profiles—and several alternative specifications.

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I. INTRODUCTION

The COVID-19 pandemic is expected to cause large and persistent output losses. According to the IMF's latest projections, global GDP levels for 2024 are approximately 5.3 percent below those projected in January 2020 for the same year.[1] Yet the pandemic has also driven the rapid adoption of new digital technologies, from teleconferencing software to e-commerce platforms. Many companies transformed their work practices, offering employees hybrid work models and offering customers contactless transactions.

Can such digitalization improve economic resilience and mitigate scarring? In principle, yes. Firms and industries harnessing digital technologies can unlock productivity gains, for instance, through automation and are better able to connect with distant customers and employees. Moreover, digitalization also improves the ability to work remotely or sell without contact, capabilities that have shielded workers and firms from the pandemic's negative effects. Simple correlations also suggest a potentially important role: estimates of output losses are higher in countries with weaker digital infrastructure (Figure 1), and the number of job posts during the pandemic fell less and recovered more quickly in digital occupations (Figure 2).

In this paper, we try to empirically investigate and quantify the role of digitalization in improving the resilience of the economy to recessions—both typical recessions and those associated with the COVID-19 pandemic. To get closer to establishing causality, we apply a difference-in-differences approach—in a local projection setting—to a large firm-level sample (consisting of 75 advanced, emerging market and developing economies from 2001Q1 to 2021Q4) and examine whether firms in more digitalized industries suffer smaller losses in sales following recessions than firms in less digitalized industries. As baseline measure of digitalization, we use the industry-wise measure of Calvino et al. (2018), who construct digitalization quartiles using Information and Communication Technology (ICT) input shares, the number of

[1] Similar figures result when using projections from the Economist Intelligence Unit and Consensus Forecasts, and when using the difference versus a simple continuation of the 2015-2019 trend instead of pre-pandemic forecasts.

robots per employee, the share of ICT specialists in total employment, and the share of turnover from online sales.[2]

Our results suggests that digitalization significantly reduces sales losses. In particular, we find that, four years after a typical recession, firms in industries that are one standard deviation more digitalized than the mean experience about 2 percent less sale losses relative to firms in industries with an average level of digitalization. This effect is economically significant and suggests a substantial role for digitalization in improving resilience and mitigating scarring. Yet it may nonetheless underestimate the true impact for the following reasons. First, in order to reduce endogeneity, we focus on pre-determined and time-invariant measures of digitalization, but even relatively less digital industries and firms increased their adoption during the pandemic.[3] This implies a potential overall effect larger than the differential effect that is detectable in our specification. Second, our sample consists of publicly listed firms, which are likely to be more digitalized than other firms not included in the sample. Finally, the role of digitalization in mitigating scarring is likely to be larger in the context of the pandemic than with previous recessions, due to the requirement for remote work and contactless sales. Indeed, when we focus on the pandemic period, early data suggest an even larger mitigation effect of digitalization—we find that already one year after the COVID-19 recession firms in industries that are one standard deviation more digitalized than the mean experience about 4 percent smaller declines in sales than other firms.

Our results are robust across a range of digitalization measures. We complement our main measure from Calvino et al. (2018) with our own measures of digital input shares, constructed using OECD input-output tables, and with intangibles shares constructed from balance sheet data. Finally, for our COVID-19 regressions we also use data on the relative frequency of digital skills on LinkedIn profiles within each industry. While no single measure can exhaustively and exclusively capture all the various dimensions of digitalization—for instance, the intangibles share may also reflect copyrights and

[2] Noting the lack of a generally accepted definition and measure of digitalization (OECD 2021a), we also use a range of alternative measures of digitalization, with similar results.

[3] Looking at the time-varying measures of digitization that we construct in the paper, we find that some of these—notably those based on OECD input-output tables—tend to increase following historical recessions. The results are available upon request.

licensing agreements—the fact that our findings are robust across this wide range of measures corroborates the role of digitalization in improving economic resilience at the firm level.

Related literature: While there is a substantial literature on digitalization as a driver of long-run growth and innovation (see Dabla-Norris et al., forthcoming), the role of digitalization during downturns is less studied. Pierri and Timmer (2020) find that unemployment rose less in US states with greater IT adoption pre-pandemic, while Bellatin and Galassi (2022) find that cities with fewer pre-pandemic job postings related to digital technologies posted fewer jobs overall during the pandemic. Our paper is most similar to Abidi et al. (2021), who investigate whether firms using websites, email, cell phones and/or foreign technology experienced smaller sales losses during the COVID-19 pandemic in 13 ME&CA economies. We contribute to this literature by providing, to the best of our knowledge, the first systematic analysis of the role of digitalization in reducing firms' revenue losses in the aftermath of various types of recessions, for a larger set of countries and firms, and across a wide range of digitalization measures.

More broadly, our paper relates to literatures on the impact of new digital technologies and on the determinants of scarring. Our paper picks up from seminal work on the impact of automation technologies (e.g., Acemoglu and Restrepo 2017, Dauth et al. 2017, Graetz and Michaels 2018), telework (e.g., Bloom et al. 2015) and e-commerce (e.g., Brynjolfsson et al. 2019). It also builds on earlier findings that increased connectivity to the internet or mobile networks can increase export sales (Freund and Weinhold 2002, 2004), reduce price dispersion (Jensen 2007) and mitigate the impact of negative shocks (Suri et al. 2012, Jack and Suri 2014).

The rest of the paper is organized as follows. Section II presents the data and Section III outlines our methodology. Section IV presents our results, first from recessions over the last twenty years and then on the initial impact of the COVID-19 pandemic. Section V presents an extensive list of robustness checks, and Section VI concludes.

II. DATA

This section describes the data used in the paper, their sources, descriptive statistics, and key stylized facts.

A. Firm-level data

Our firm-level data comes from S&P Capital IQ. The database provides extensive balance sheet and income statement information at the firm-level and at the quarterly frequency. It covers a large, unbalanced sample of 150 countries from 1950Q1 to 2021Q2; in order to reduce significant gaps in the time series, we restrict the sample to 2001Q1 onwards. This leaves us with a sample of 75 countries. Details regarding the sample of countries used in the analysis, by geographic region, are available in Table A1.1 of Annex 1. The data is restricted to non-financial corporations and cleaned to remove firms which had negative values for assets or debt in any year, and observations with the incorrect sign for revenue, capital expenditure, cash, tangible assets, and interest expenditure were set to missing (see Kim et al. 2020, and Arbatli-Saxegaard et al. 2022, for details). We further restrict the sample to exclude real estate and insurance companies. Tables A1.2 and A1.3 display the number of firms across countries and 20 economic sectors.

For our revenue measure, we use total revenue (IQ_TOTAL_REV), Table A1.4 displays the summary statistics for this variable. For our intangibles measure, we use intangible assets (IQ_GW_INTAN) as a share of total assets (IQ_TOTAL_ASSETS). All firm-level variables have been winsorized at the 1st and 99th percentiles to eliminate outliers.

B. Recessions and other macroeconomic data

Our baseline measure for recessions is the start of a technical recession, defined by two consecutive quarters of negative GDP growth. Quarterly real gross domestic product growth from Haver Analytics is the main source used to construct this variable, but we complement it with World Economic Outlook (WEO) data for countries that have limited data in Haver. For these countries, we replace the full country series with WEO data. We then define a dummy where the first observation for each country's recession episode is set to 1. This leaves us with a total of 231 recessions for advanced economies and 336 for emerging market and developing economies.

We also use two alternative measures to complement our recession indicators: banking and currency crisis dummies from the Global Crises Data of Reinhart and Rogoff (2009). Recession data summary statistics are reported in Table A1.5.

C. Digitalization measures

There is not yet a generally accepted definition and measure of digitalization, though substantial work is ongoing to agree on a consistent international approach (OECD 2021a). This reflects the pervasive nature of the technologies and the activities involving them, from physical computers to data streaming to real-world transactions mediated through e-commerce platforms (e.g., taxi rides and room rentals). We therefore adopt a pluralist approach, drawing on a range of sources to capture different facets of digitalization. In this section we outline a series of alternative digitalization measures D^m which we use in the main specification and the robustness checks.

First, our baseline measure D_r^C is an industry-wise digitalization quartile, constructed by Calvino et al. (2018) using data on ICT input shares, the number of robots per employee, the share of ICT specialists in total employment, and the share of turnover from online sales. This 'off-the-shelf' measure has several advantages: in addition to being time-invariant, and therefore exogenous to recessions, it is independently constructed and draws on a wide range of data sources to capture and synthesize several facets of digitalization—namely purchases of digital tools themselves, investment in the human capital required to embed them in production, and the exploitation of digital channels for transacting with customers. This composite and relative approach, based on digitalization quartiles rather than absolute values, also produces sector-wise estimates that remain accurate over time. For instance, Calvino et al. (2018) find that only 17 percent of sectors would change their relative digitalization quartile, if it were recalculated separately in 2001-03 and 2013-15. This suggests that the approach produces relevant estimates across the whole timespan of our study, reflecting fundamentals rather than volatile sub-categories of digitalization technologies.

Nonetheless, there remain limitations to this measure. Given that several different metrics are used to construct the composite, the Calvino et al. (2018) method is relatively demanding on data availability. It only uses data from 12 developed countries—so does not take into account various country specificities when constructing the industry-wise average. We therefore complement this measure by constructing our own country-industry-specific measures using information from harmonized input-output tables. First, we construct a measure $D_{r,i}^{ICIO} = \sum_l \alpha_{rli} \cdot D_l$ based on direct ICT input shares, where α_{rli} is the input share of industry l in industry r country i, and $D_l = 1$ for "Computer, electronic and optical products" and "IT and other information activities".[4] To construct this measure, we use consolidated data from 66 countries via the OECD Inter-Country Input-Output Tables (OECD 2021b).[5] Specifically, this measures the share of each industry's direct inputs that come from narrowly defined ICT industries. Second, we note that digitalization can also be a property of broader supply chains, where what matters is the extent to which suppliers and their suppliers in turn also use digital inputs. We therefore calculate a second measure $D_{r,i}^{TiVA} = \sum_l \zeta_{rli} \cdot D_l$ where ζ_{rli} is the share of total input value added of industry r country i that comes from industry l.[6] This uses data from the OECD Trade in Value Added database (OECD 2021c), again for 66 countries. $D_{r,i}^{TiVA}$ therefore repeats $D_{r,i}^{ICIO}$ but drawing on digital inputs in all stages in production, not just in direct inputs. Intuitively, it measures the total dependence of industry r on narrowly defined ICT industries, both as direct inputs to production, and as inputs to other inputs to production, and so on.

Together, these input-output table measures provide a good gauge of the relative dependence of sectors on both physical IT hardware and digital services. The set of countries used to construct them, however, is still not identical to that for which we have

[4] For each country-industry cell we take the median value across the available years 2001-2015 to create a comparable time-invariant measure.

[5] The range of countries includes all OECD, EU and G20 countries, and a selection of economies from East Asia, Southeast Asia, and South America.

[6] Again, for each country-industry we take the median value across the available years, in this case 2001-2018, to create a comparable time-invariant measure.

firm revenue data in Capital IQ. We therefore construct a further measure $D_{r,i}^{Int}$ which is the median share of intangible assets among firms within a country-industry cell, calculated using the same Capital IQ balance sheets.[7] While intangibles as listed on balance sheets are an imperfect measure of digitalization, since they contain other elements such as copyrights, licensing agreements and post-merger goodwill (see, for instance, Haskel and Westlake 2018), this provides an additional robustness check for a larger set of countries.

Finally, for the pandemic period we use recent data from LinkedIn profiles to create an alternative digitalization measure focused on human capital. We define:

$$D_{r,i}^{TechSkills} = \sum_{o} w_{o,r,i} \cdot \frac{1}{50}(TechSkillsInTop50_{o,r,i})$$

where $TechSkillsInTop50_o$ is the number of skills categorized as 'tech skills' appearing in the top 50 skills listed by workers in each occupation o and industry-country ri, and $w_{o,r,i}$ is the relative weight of each occupation in the total employment of each industry-country ri. Intuitively, this measures the relative intensity of digital skills among all those skills used by each country and industry pair.[8] Digitalization measures summary statistics are reported in Table A1.6.

Table 1 shows the cross-correlations between these various measures of digitalization, and Table A1.7 shows the most and least digital sectors according to each of the rankings. In general, the measures are strongly positively correlated and rank sectors in an intuitive manner. Between them they capture the major facets of digitalization and reassure us that our conclusions are not driven by a narrow range of technologies (for instance, industrial robotics or mobile internet) but instead accurately reflect the widespread impacts of the broad concept of digitalization.

[7] To construct a comparable country-industry measure, we first calculate the median share of intangibles within each firm over 2001-2021, then we take the median across those firms within a country-industry cell. This country-industry-level approach also has the advantage of reducing distortions arising from the large share of firms (approximately 60%) that do not report intangibles data in their balance sheets.

[8] LinkedIn calculate this intensity measure across the whole period for which data is available, specifically 2016Q1 to 2022Q1, for 20 broad industries across 40 countries.

III. EMPIRICAL METHODOLOGY

We use Jordà's (2005) local projection method to estimate the short- and medium-term firm revenue effects of recessions, and how they are shaped by the extent of digitalization. We proceed in two steps. First, we estimate the average (unconditional) effect of recessions on firm revenue using the following specification:

$$\Delta y_{n,i,t+k} = \alpha_{is}^{k} + \gamma_{nq}^{k} + \sum_{j=-k}^{4} \mu_j^k R_{i,t-j} + \sum_{j=1}^{4} \theta_j^k \Delta y_{n,i,t-j} + \varepsilon_{n,i,t}^{k} \qquad \forall k = 0,1, \dots 15 \tag{1}$$

where the dependent variable $\Delta y_{n,i,t+k}$, is the log difference in revenue of firm *n* from country *i* at quarterly date *t* over *k* quarters, $R_{i,t}$ is a dummy that denotes the beginning of a technical recession—defined as two quarters of consecutive of GDP growth—in country *i* at time *t*, and μ_j^k denotes the average firm's response of revenue to recessions after *k* quarters. γ_{nq} indicates firm-quarters dummies to control for unobservable time-invariant firm characteristics as well as firm-specific seasonality in the level of revenue; α_{is}^k are country-sector fixed effects to account for cross-sector variations across countries—such as country-specific comparative advantages in specific sectors. Following Teulings and Zubanov (2014), we also include leads of the recession variable in our regressions to control for recessions that fall in the horizon of the local projection.

In the second step, we extend equation (1) to estimate how the dynamic effect of recessions on revenues varies across firms depending on the extent of sectoral digitalization. We estimate the following specification:

$$\Delta y_{n,i,t+k} = \alpha_{ist}^{k} + \gamma_{nq}^{k} + \sum_{j=-k}^{4} \mu_j^k R_{i,t-j} * D^m + \sum_{j=1}^{4} \theta_j^k \Delta y_{n,i,t-j} + \varepsilon_{n,i,t}^{k} \qquad \forall k = 0,1, \dots 15 \tag{2}$$

where D^m is a placeholder for a digitalization measure, which in our baseline specification is the Calvino et al. (2018) measure D_r^C described in the previous section. We use this time-invariant industry-wise variable to avoid endogeneity due to the potential time-varying response of digitalization to recessions, and in particular to the pandemic. α_{ist}^k are country-sector-time fixed effects to account for macroeconomic shocks and their differential effects across sectors (e.g., the differential effect of recessions) as well as sector-specific shocks at the country level (e.g., changes in national policies to support a particular sector).[9] In our baseline specification, μ_j^k indicates the marginal additional response of revenue to recessions in quarter *t+k* for firms in industries with a degree of digitalization one standard deviation above the mean, relative to firms in industries with an average level of digitalization. Specifically, μ_j^k reflects the change in log revenue over horizon *k*, which is approximately equal to the additional cumulative growth rate of revenue in these firms over horizon *t+k*. In the figures, we show this in percentage point terms, i.e. $\mu_j^k \times 100$.

In both specifications (1) and (2), we cluster standard errors by firm and country-time. We use a panel of over 24,000 firms for the period 2001Q1 to 2021Q1, for a total of more than 800,000 observations. In our robustness checks, we consider a range of alternative digitalization and recession variables, various alternative sub-samples, and an alternative estimation methodology.

For our specific analysis of the pandemic, we drop all data before 2016, and set the recession dummy $R_{i,t}$ to zero before 2019Q4. We do this to exclusively focus on recessions associated with the COVID-19 pandemic as well as to have enough quarters to controls for pre-pandemic trends. Since nearly all pandemic recessions occurred at the same time–specifically in 2020Q1–we also adjust the fixed effects to account for the fact that $R_{i,t}$ effectively only varies over time. We therefore drop the fixed effect α_{ist}^k in the previous specification and replace it with country-time and country-industry fixed effects α_{it}^k and α_{ir}^k. Thus, while we loosen the fixed effects in one respect, by dropping the

[9] Note that we distinguish between a broad sector s and an industry r, with the latter nested within the former. Our Capital IQ dataset includes 20 sectors and 60 industries, so controlling for country-sector-time fixed effects does not preclude our use of a country-industry-time-varying explanatory variable. Indeed, Table A1.8 in the Annex shows that when regressing the digitalization measures on country-sector-time fixed effects the R-squared remains low – i.e., most of the variation in digitalization occurs within-sector but across industries.

country-sector-time fixed effect, we also tighten them in another, by controlling for industry-level variation rather than (the more aggregate) sector-level variation.

Finally, for our analysis using industry-wise hiring and worker transitions data from LinkedIn, we convert our specification to the industry level. Specifically, we estimate:

$$\Delta y_{r,i,t+k} = \alpha_{it}^{k} + \alpha_{ri}^{k} + \sum_{j=-k}^{4} \mu_j^k R_{i,t-j} * D^m + \sum_{j=1}^{4} \theta_j^k \Delta y_{r,i,t-k} + \epsilon_{r,i,t} \quad (3)$$

$$\forall k = 0,1 \dots 15$$

where $\Delta y_{r,i,t+k}$ is the change in log hiring in or transitions into/out of industry *r* over *k* quarters, α_{it}^{k} are country-time fixed effects and α_{ri}^{k} are industry-country fixed effects. We cluster at the country level and use quarterly data for 20 industries from 40 countries over the period 2016Q1 to 2022Q1, for a total of approximately 7000 observations.

IV. Results

This section first presents the results of our analysis using all recessions since 2001, then focusses specifically on the recessions caused by the COVID-19 pandemic.

A. Historical Recessions

Figure 3 presents the evolution of log revenue following a recession episode. The solid line displays the average estimated response, while dotted and dashed regions denote the 90 and 68 percent confidence bands respectively. We find that recessions are associated with persistent effects on the level of revenue relative to pre-recession trends. In particular, the average recession in our sample is associated with a reduction in the level of revenue by more than 10 percent four quarters after the recession and by 5 percent after 8 quarters.

Figure 4 is analogous to Figure 3 but reports the differential response of revenue to recessions between a firm in a relatively digitalized industry and a firm in an average industry. The figure shows that firms in industries that are one standard deviation more digitalized than the mean experience 1 percent lower revenue losses after two years. The difference is larger (about 2 percent) and highly statistically significant four years after the recession, highlighting that companies with higher digitalization levels are more resilient to economic shocks over the medium term.

B. The COVID-19 Pandemic

Digitalization could be even more important during recessions caused by the COVID-19 pandemic. Governments, firms, and individuals had to adapt to lockdowns and social distancing measures that have had deep and lasting effects on work and consumption practices. Digitalization became an important channel to mitigate harms from pandemic-response measures, in particular by facilitating remote work and contactless sales.

To examine the impact of COVID-19 period recessions on firms' revenue, we use our baseline recession dummy—the start of two periods of negative growth—and artificially restrict it to be equal to one only for those recessions begun on or after 2019Q4.[10] We also restrict the overall sample to 2016Q1 onwards so that our fixed effects are only estimated from a relevant timespan. Figure 5 presents the evolution of log revenue following a COVID-19 recession episode. COVID-19 recessions are associated with persistent effects on the level of revenue, of up to 20 percent after five quarters—a magnitude almost four times that associated with a typical recession, reflecting the severity and the unprecedented nature of the pandemic.

Figure 6 reports the differential response of revenue to COVID-19 recessions for a firm in an industry with one standard deviation higher digitalization than the average. Revenue in such is almost 4 percent higher four quarters after a recession and increases to close to 5 percent after five quarters. This effect is statistically significant and precisely estimated, and more than four times larger than the corresponding effect of an average historical recession after five quarters. Thus, the data strongly support the idea that

[10] Any recession that occurred before 2019Q4 is artificially set to zero. This likely produces an underestimation of the true effect of digitalization as the counterfactual in our diff-in-diff approach also includes recessions prior to the COVID-19 period.

digitalization has been especially important during the COVID-19 pandemic recession, given the unprecedented measures introduced to reduce mobility and social contact.

This higher revenue growth may also have allowed firms in more digitalized industries to expand relative to other firms. Figure 7 shows the differential effect of COVID-19 recessions on growth in hiring rates and total transitions by workers into and out of each industry, using industry-level outcome variables from LinkedIn. Panel A shows that hiring rates in highly digitalized industries grew almost 3 percent faster than in average industries in the year after the COVID-19 recession, and almost 4 percent faster after two years. Similarly, Panels B and Panel C show that the inflow (outflow) of workers to (from) highly digitalized industries grew more than 3 percent faster (1 percent slower) than in other industries in the two years after the shock.

V. Robustness Checks

This section provides several robustness checks to demonstrate the generality of our results. We provide four types of checks, using: i) alternative digitalization measures; ii) alternative recession definitions; iii) alternative samples; and iv) an alternative methodology.

A. Alternative digitalization measures

While the effects of digitalization on our professional and personal lives—and on broader society and the economy—are clearly visible, its measurement is not straightforward. There is not yet a clear consensus on how to define and measure the concept (OECD, 2021). To account for this, in this paper we take a pluralist approach and, as a first robustness check, we examine the sensitivity of our results to several measures of digitalization as described in Section II.

Figure 8 shows the differential effect of recessions on revenue growth using digitalization measures defined at the country-industry level. Panel A shows results using $D_{r,i}^{ICIO}$, the share of direct digital inputs, constructed from OECD Inter-Country Input-Output tables (OECD 2021b). Panel B shows results using $D_{r,i}^{TiVA}$, the digital share of total input value added, constructed from the OECD Trade in Value Added database

(OECD 2021c). Panel C shows results using $D_{r,i}^{Int}$, the average share of intangible assets, constructed using Capital IQ balance sheet data. Results are qualitatively robust, with firms in more digital country-industries facing 1-2 percent less revenue losses four years after recessions, though the differential effect is less precisely estimated.

Since the OECD input-output tables are calculated every year for a consistent and balanced panel of country-industries, we can also construct time-varying versions of these measures. Figure 9 shows the results, first using the contemporaneous values of $D_{r,i,t}^{ICIO}$ and $D_{r,i,t}^{TiVA}$, then using lagged versions $D_{r,i,t-1}^{ICIO}$ and $D_{r,i,t-1}^{TiVA}$ to mitigate potential endogeneity.[11] Our main findings are qualitatively robust in all cases.

Lastly, we check that our pandemic-specific results also hold when using alternative digitalization measures. For this shorter period, we can also use the additional digitalization measure $D_{r,i}^{TechSkills}$ calculated from the skills listed on LinkedIn profiles, as described in Section II. Figure 10 shows that our main findings are robust to these checks—except for Panel C, using the intangibles share, which we speculate may reflect the particular pressures facing firms with a high share of intangibles (which includes post-merger goodwill and potential goodwill impairment) in the boom/bust turmoil of pandemic-era merger activity.

B. Alternative recession dummies

We next look at the sensitivity of our results to the definition of recessions. While our baseline approach follows the standard technical definition of recessions, we also consider alternative versions, specifically the start of a currency crisis, or the start of a banking and currency crisis. The results produced using these variables are very similar to those in the baseline specification, with marginally larger effects over four years (Figure 11). This similar response to these alternative recessions emphasizes the generality of the role played by digitalization in fostering resilience.

[11] Specifically, industries may respond to recessions by increasing their use of digital tools, and this may be particularly feasible for industries whose sales have been least harmed by the recession – which would generate a misleading positive relationship between digitalization and revenue growth.

C. Alternative samples

We next examine the sensitivity of our results to alternative samples. A noted above, the restrictions imposed by countries in response to the COVID-19 pandemic triggered an economic crisis with peculiar characteristics. Digitalization and telework both played an important role in mitigating the effects of this crises among companies, since it allowed them to continue their activity by reducing the disruption to their work. Therefore, we first check whether our results from historical recessions are driven by this specific crisis episode. Figure A2.1 Panel A in Annex 2 shows our baseline results excluding the year 2020 from our regression. Our results remain similar to our baseline, confirming that digitalization already mitigated the effects of recessions even before the COVID-19 pandemic.

Second, we look at whether the results are driven by other major crisis episodes, such as the 2008 Global Financial Crisis or other systemic banking crises. The results reported in Figure A2.1 panels B and C confirm that the differential response of revenue for firms in more digitalized industries remains similar to, and not statistically different from, the baseline.

Third, we check whether the results are driven by specific countries or groups of countries. To this end, we re-estimate equation (2) but excluding one country at a time or one region at a time. The results, reported in Figure A2.2 and A2.3 of Annex 2, suggest that our baseline results are not dependent on any specific country or group of countries. Similarly, we repeat this test for industries, excluding one 2-digit sector at a time, with the same result (Figure A2.4 of Annex 2).

Fourth we also check whether the results change depending on countries' income levels. Figure A2.5 of Annex 2shows the differential effect of recessions between highly digitalized firms and the average firm restricting the sample to Advanced (left panel) and Emerging Economies (right panel). The results show almost no difference between the overall effect and the effect depending on countries' income levels, revealing that digitalization serves as a buffer for these economic shocks independently of countries' income characteristics.

Finally, we investigate whether our results are sensitive to our choice of winsorization threshold. We therefore winsorize 0.05 and 5 percent of the tails of the distribution of our dependent variable, allowing in turn a greater or lesser role for extreme observations than in our baseline. The results obtained are again similar to the baseline (Figure A2.6).

D. Alternative methodology

In a final robustness check, we repeat our pandemic results using an alternative difference-in-differences specification following Duval et al. (2020). This focuses on changes in firm and industry behavior around a single specified date, which in our case is the onset of the global pandemic in 2020Q1, rather than allowing for country-specific variation in the timing of pandemic recessions $R_{i,t}$, as in our local projection specifications.

For the Capital IQ firms, we calculate the growth in average quarterly revenue between the two years pre-pandemic and the first year post-pandemic, and how it varies with the degree of digitalization of the industry:

$$\Delta y_{n,i} = \mathrm{\alpha_i} + \alpha_s + \mu * D_r^C + \epsilon_{n,i} \quad (4)$$

where $\Delta y_{n,i}$ is firm n's log average quarterly revenue in the post-pandemic period (2020Q2-2021Q1) minus log average quarterly revenue in the pre-pandemic period (2017-2019), D_r^C is the standardized Calvino et al. (2018) measure of digitalization in industry r, and $\mathrm{\alpha_i}$ and α_s are country and sector fixed effects respectively. For the alternative industry-wise outcome variables from LinkedIn, we run a similar specification but drop the sector fixed effects due to the less granular industry classification available in the LinkedIn data:

$$\Delta y_{r,i} = \mathrm{\alpha_i} + \mu * D_r^C + \epsilon_{r,i} \quad (5)$$

where $y_{r,i}$ is now the log of average hiring rates or transitions into or out of the industry. The results for this exercise are shown in Figure A2.7 of Annex 2. We again find similar effects to the baseline, with an approximately 2 percentage point rise in revenue growth post-pandemic, along with 3 percentage point higher growth in transitions into more digitalized industries, and roughly 1 percentage point lower growth in transitions out of such industries.

VI. Conclusion

The COVID-19 pandemic is expected to have substantial and persistent negative effects on economic activity. Yet it has also driven a rapid acceleration in adoption of digital technologies and digitally enabled work practices, such as teleconferencing and hybrid work schedules. Using quarterly firm-level balance sheet data from 75 countries, we find that higher digitalization *ex ante* is associated with lower medium-term firm revenue losses. Moreover, when focusing on early data since the pandemic, we find evidence of an even larger role—consistent with the particular importance of digital communication technologies in circumstances of widespread social distancing. Drawing on data from LinkedIn profiles, we find that more digitalized industries had higher hiring rates in the two years after pandemic-induced recessions, and experienced greater net inflows—again consistent with digitalization mitigating scarring and improving firm resilience.

These results are robust across a wide range of measures of digitalization, as well as several alternative specifications. Together, they highlight that—beyond the classical story of new technologies supporting growth and innovation in the long run—digitalization can also help prevent and reduce the harmful effects of economic downturns in the medium run. In doing so, our results provide further support for efforts to promote the widespread adoption of digital technologies, above and beyond the boost already provided by forced adoption during the COVID-19 pandemic.

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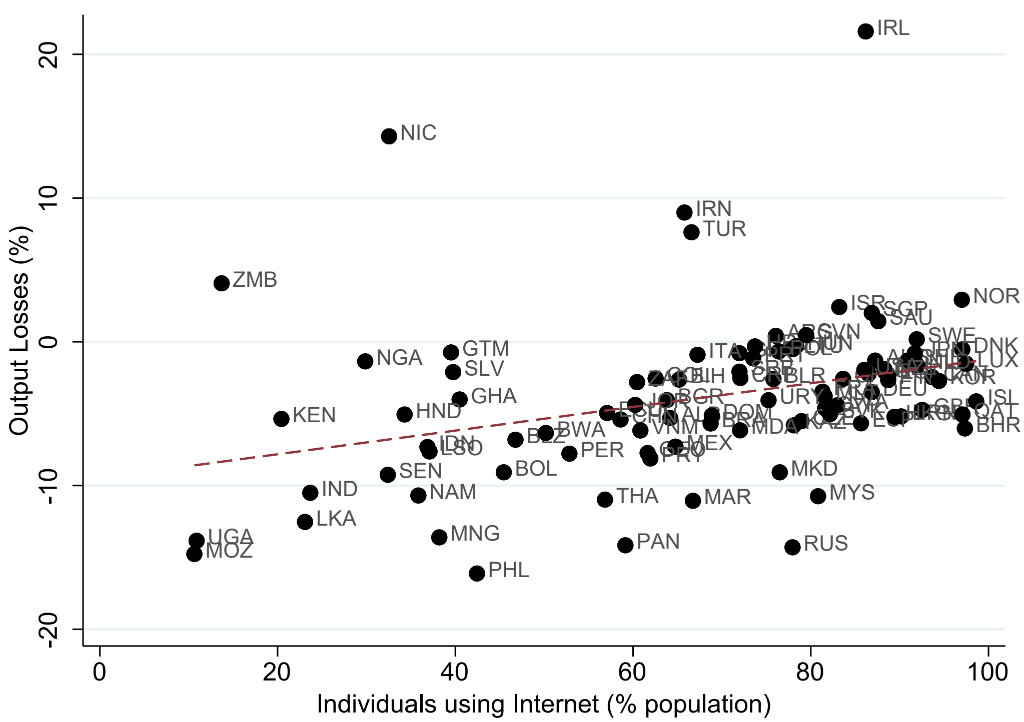
Tables and Figures

Table 1. Correlation between digitalization measures

	Calvino	ICIO	TIVA	Intangibles	LinkedIn Digital Skills
Calvino	1				
ICIO	0.4*	1			
TIVA	0.3*	1*	1		
Intangibles	0.4*	0.3*	0.4*	1	
Digital Skills	0.5*	0.5*	0.4*	0.5*	1

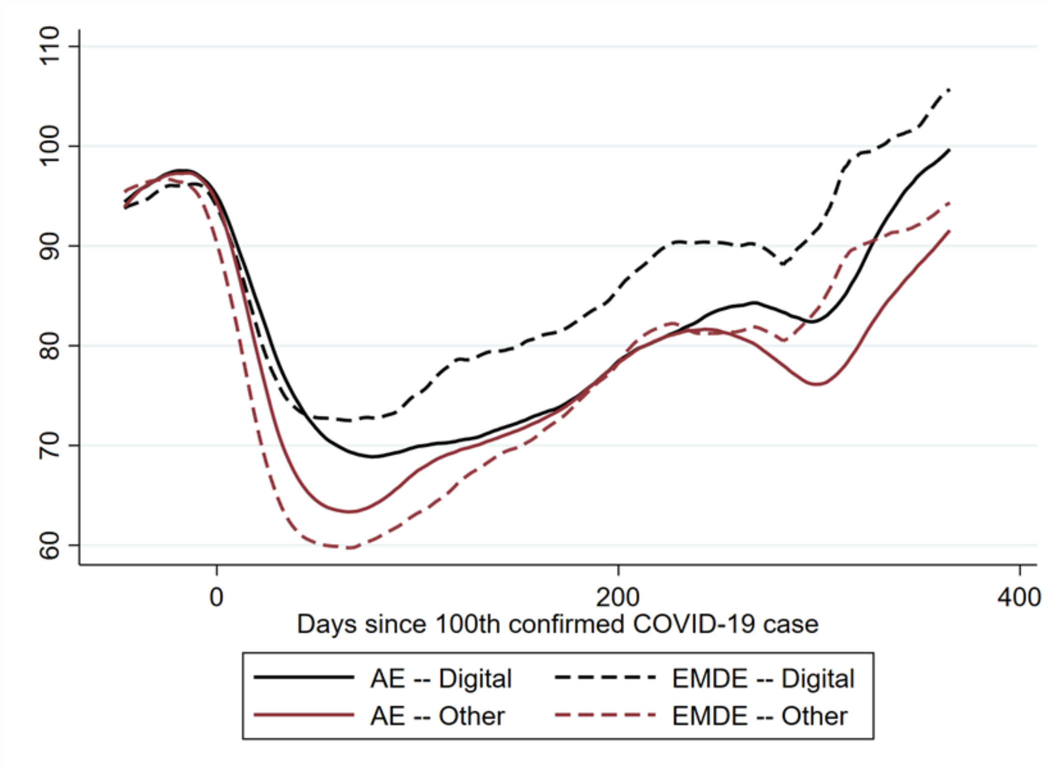
Note: Pairwise correlation coefficients. Collapsed to industry level by median. * Significant at 5% level.

Figure 1: Scarring and Internet Access (Percent)



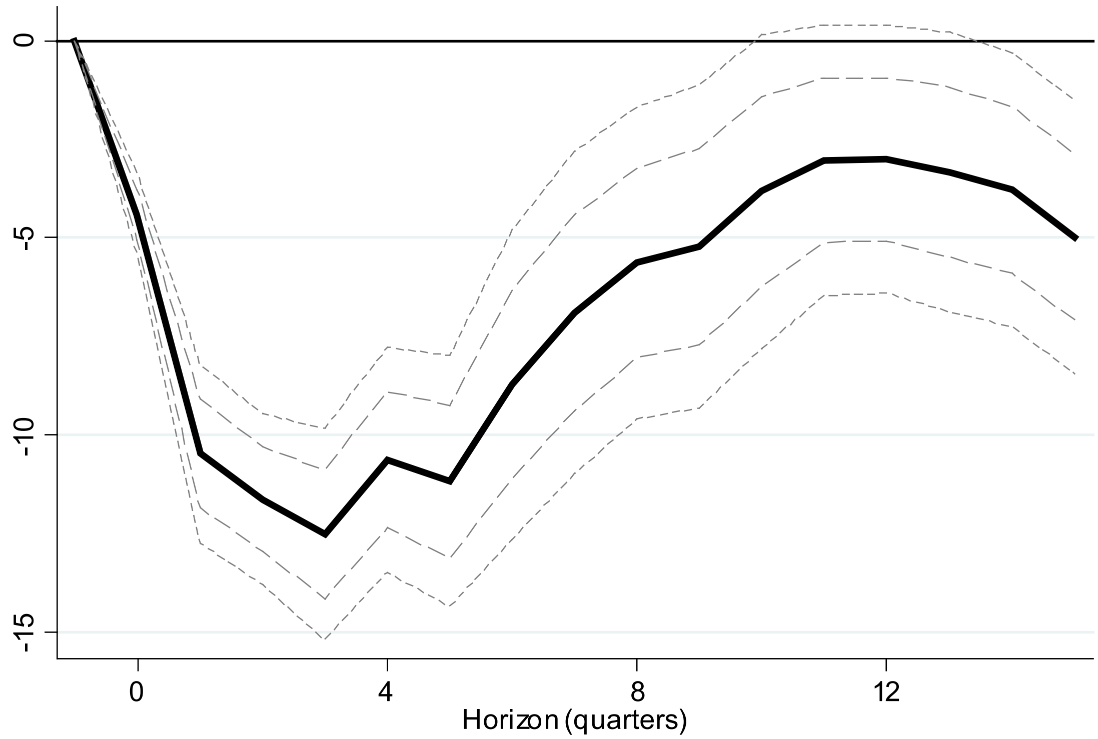
Source: World Economic Outlook and World Bank Development Indicators.
Note: Output losses are computed as the percent deviation
between pre-pandemic (January 2020) and latest GDP projections for 2024

Figure 2: Job Posts by Income Group (30-day MA, indexed to January + February 2020)



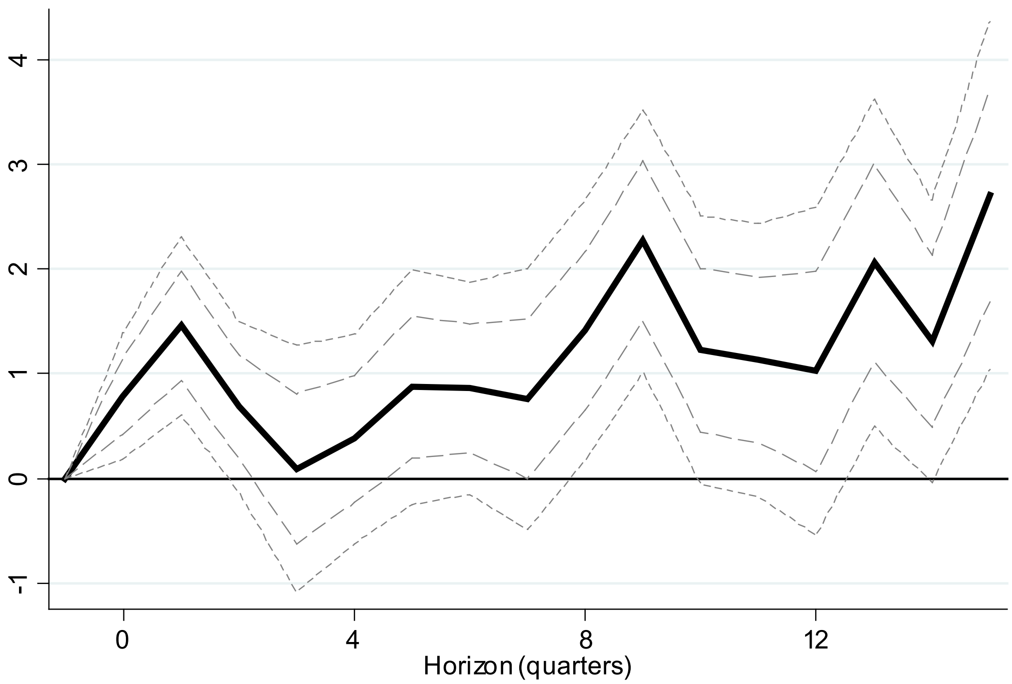
Source: Indeed.com and authors' calculations. Sample contains daily job counts of total job posts for 35 countries.

Figure 3: Unconditional effect of recessions on changes in (log) revenue



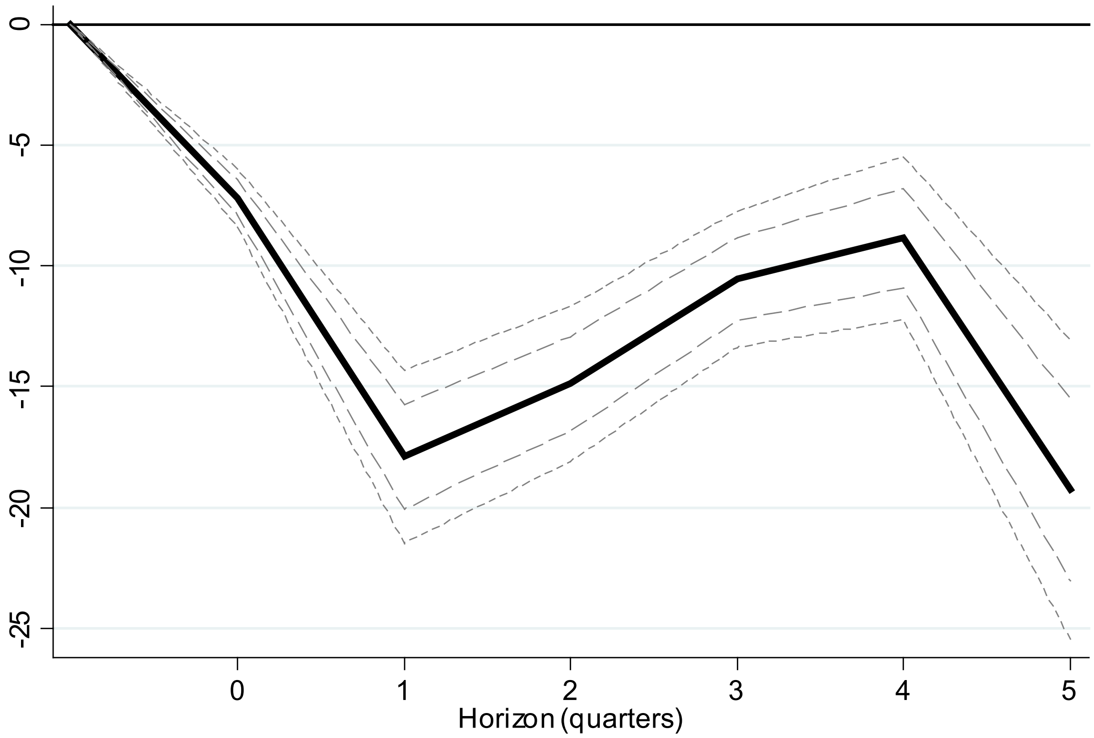
Note: Impulse response function based on local projection methods following Jordà (2005) using firm-level quarterly data from 75 countries for the period 2001Q1 to 2021Q1. Estimates based on the regression $\Delta y_{n,i,t+k} = \alpha_{is}^k + \gamma_{nq}^k + \sum_{j=-k}^{4} \mu_j^k R_{i,t-j} + \sum_{j=1}^{4} \theta_j^k \Delta y_{n,i,t-j} + \varepsilon_{n,i,t}^k$ for different horizons k, where $\Delta y_{n,i,t+k}$ is the log change in revenue of firm n in country i at time t over the next k quarters, $R_{i,t}$ is a dummy which takes value 1 at the start of a technical recession, α_{nq}^k are firm-quarter fixed effects, and α_{is}^k are country-sector fixed effects. The regression is estimated separately for different horizons k over a four-year period. The solid line shows the point estimate for μ^k for different horizons k, while the dashed and dotted lines are the 68 percent and 90 percent confidence intervals respectively. Standard errors are clustered by firm and country-time.

Figure 4: Differential Effect of Recession on log Revenue for Highly Digitalized Industries Vs. Average



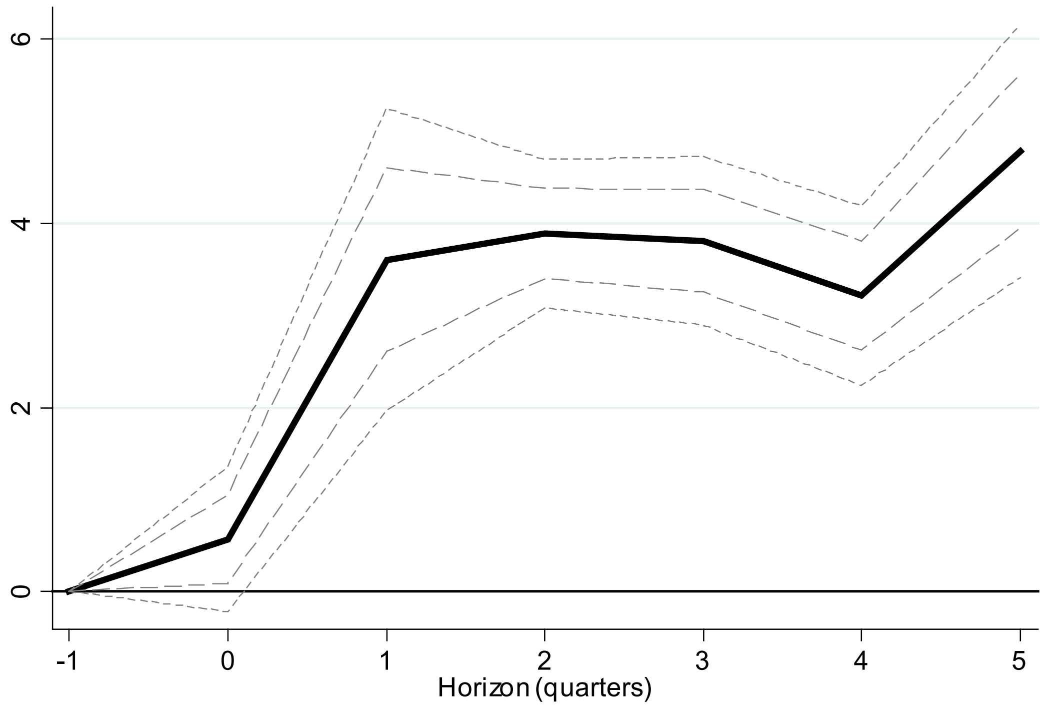
Note: Impulse response function based on local projection methods following Jordà (2005) using firm-level quarterly data from 75 countries for the period 2001Q1 to 2021Q1. Estimates based on the regression $\Delta y_{n,i,t+k} = \alpha_{ist}^k + \gamma_{nq}^k + \sum_{j=-k}^{4} \mu_j^k R_{i,t-j} * D^m + \sum_{j=1}^{4} \theta_j^k \Delta y_{n,i,t-j} + \varepsilon_{n,i,t}^k$ for different horizons k, where $\Delta y_{n,i,t+k}$ is the log change in revenue of firm n in country i at time t over the next k quarters, $R_{\mathrm{i},t}$ is a dummy which takes value 1 at the start of a technical recession, $D^m = D_r^C$ is the standardized value of the Calvino et al. (2018) measure of industry-wise digitalization, α_{nq}^k are firm-quarter fixed effects, and α_{ist}^k are country-sector-time fixed effects. The regression is estimated separately for different horizons k over a four-year period. The solid line shows the point estimate for μ^k for different horizons k, while the dashed and dotted lines are the 68 percent and 90 percent confidence intervals respectively. Standard errors are clustered by firm and country-time.

Figure 5: Unconditional effect of COVID-19 recessions on log revenue



Note: Impulse response function based on local projection methods following Jordà (2005) using firm-level quarterly data from 75 countries for the period 2016Q1 to 2021Q1. Estimates based on the regression $\Delta y_{n,i,t+k} = \alpha_{is}^k + \gamma_{nq}^k + \sum_{j=-k}^{4} \mu_j^k R_{i,t-j} + \sum_{j=1}^{4} \theta_j^k \Delta y_{n,i,t-j} + \varepsilon_{n,i,t}^k$ for different horizons k, where $\Delta y_{n,i,t+k}$ is the log change in revenue of firm n in country i at time t over the next k quarters, $R_{i,t}$ is a dummy which takes value 1 at the start of a technical recession from 2019Q4 onwards, α_{nq}^k are firm-quarter fixed effects, and α_{is}^k are country-sector fixed effects. The regression is estimated separately for different horizons k over a five-quarter period. The solid line shows the point estimate for μ^k for different horizons k, while the dashed and dotted lines are the 68 percent and 90 percent confidence intervals respectively. Standard errors are clustered by firm and country-time.

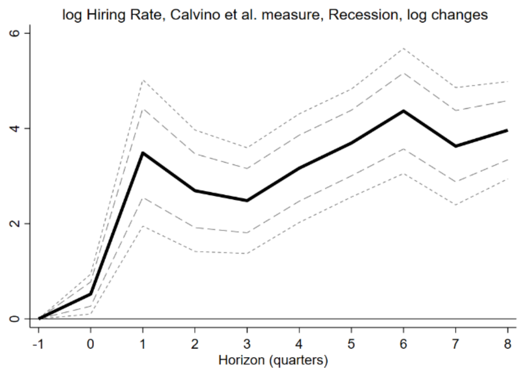
Figure 6: Differential Effect of COVID-19 Recession on log Revenue for Highly Digitalized Industries Vs. Average



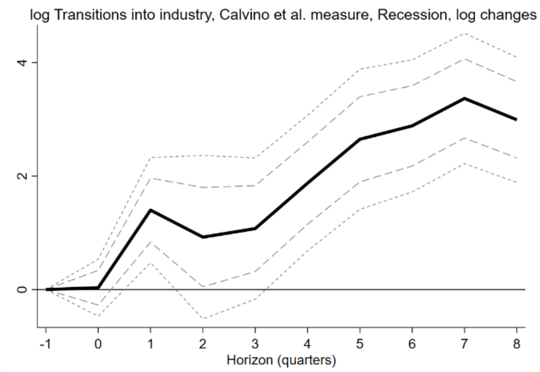
Note: Impulse response function based on local projection methods following Jordà (2005) using firm-level quarterly data from 75 countries for the period 2016Q1 to 2021Q1. Estimates based on the regression $\Delta y_{n,i,t+k} = \alpha_{ist}^{k} + \gamma_{nq}^{k} + \sum_{j=-k}^{4} \mu_j^k R_{i,t-j} * D^m + \sum_{j=1}^{4} \theta_j^k \Delta y_{n,i,t-j} + \varepsilon_{n,i,t}^{k}$ for different horizons k, where $\Delta y_{n,i,t+k}$ is the log change in revenue of firm n in country i at time t over the next k quarters, $R_{\mathrm{i},t}$ is a dummy which takes value 1 at the start of a technical recession from 2019Q4 onwards, $D^m = D_r^C$ is the standardized value of the Calvino et al. (2018) measure of industry-wise digitalization, α_{nq}^{k} are firm-quarter fixed effects, and α_{ist}^{k} are country-sector-time fixed effects. The regression is estimated separately for different horizons k over a five-quarter period. The solid line shows the point estimate for μ^k for different horizons k, while the dashed and dotted lines are the 68 percent and 90 percent confidence intervals respectively. Standard errors are clustered by firm and country-time.

Figure 7: Differential Effect of COVID-19 Recession on log Hiring Rates and Workers Transition for Highly Digitalized Industries Vs. Average.

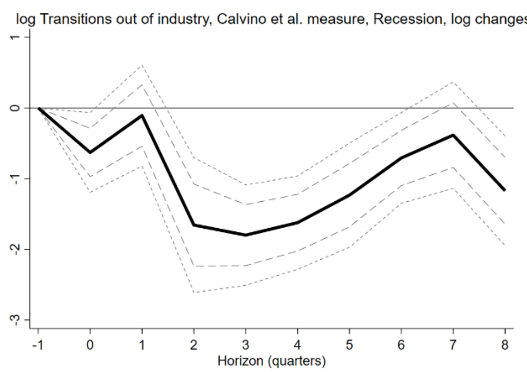
Panel A: Log Hiring Rate



Panel B: Log Transitions into Industry



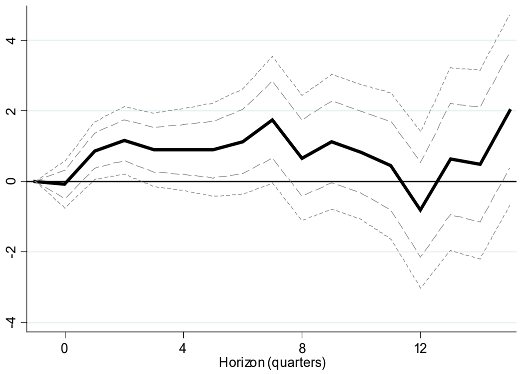
Panel C: Log Transitions out of Industry



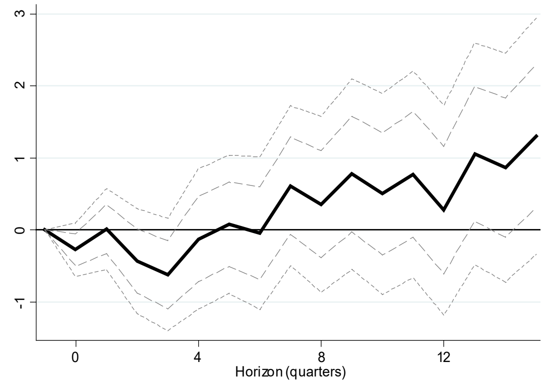
Note: Impulse response function based on local projection methods following Jordà (2005) using industry-level quarterly data from 40 countries for the period 2016Q1 to 2022Q1. Estimates based on the regression $\Delta y_{r,i,t+k} = \alpha_{it}^{k} + \alpha_{ri}^{k} + \sum_{j=-k}^{4} \mu_j^k R_{i,t-j} * D^m + \sum_{j=1}^{4} \theta_j^k \Delta y_{r,i,t-k} + \epsilon_{r,i,t}$ for different horizons k, where $\Delta y_{r,i,t+k}$ is the change in log hiring in or transitions into/out of industry r over k quarters, $R_{\mathrm{i},t}$ is a dummy which takes value 1 at the start of a technical recession from 2019Q4 onwards, $D^m = D_r^C$ is the standardized value of the Calvino et al. (2018) measure of industry-wise digitalization, α_{it}^{k} are country-time fixed effects and α_{ri}^{k} are industry-country fixed effects. The regression is estimated separately for different horizons k over a two-year period. The solid line shows the point estimate for μ^k for different horizons k, while the dashed and dotted lines are the 68 percent and 90 percent confidence intervals respectively. Standard errors are clustered at the country level.

Figure 8: Robustness: Country-Industry Alternative Digitalization Measures

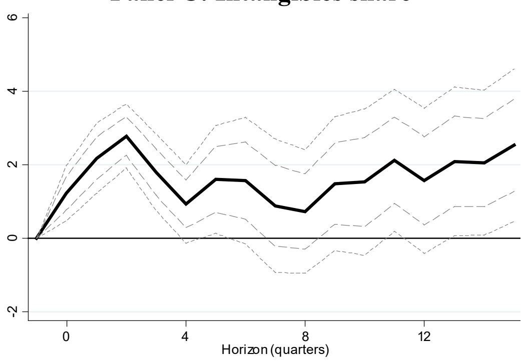
Panel A: ICIO
(Direct digital inputs)



Panel B: TiVA
(Total value added from digital inputs)



Panel C: Intangibles share

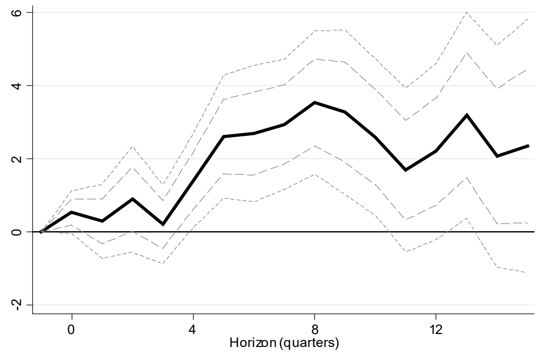


Note: Impulse response function based on local projection methods following Jordà (2005) using firm-level quarterly data from 75 countries for the period 2001Q1 to 2021Q1. Estimates based on the regression $\Delta y_{n,i,t+k} = \alpha_{ist}^{k} + \gamma_{nq}^{k} + \sum_{j=-k}^{4} \mu_j^k R_{i,t-j} * D^m + \sum_{j=1}^{4} \theta_j^k \Delta y_{n,i,t-j} + \varepsilon_{n,i,t}^{k}$ for different horizons k, where $\Delta y_{n,i,t+k}$ is the log change in revenue of firm n in country i at time t over the next k quarters, $R_{i,t}$ is a dummy which takes value 1 at the start of a technical recession, $D^m \in \{D_{r,i}^{ICIO}, D_{r,i}^{TiVA}, D_{r,i}^{Int}\}$ is the standardized value of an alternative country-industry-level measure of digitalization, α_{nq}^{k} are firm-quarter fixed effects, and α_{ist}^{k} are country-sector-time fixed effects. The regression is estimated separately for different horizons k over a four-year period. The solid line shows the point estimate for μ^k for different horizons k, while the dashed and dotted lines are the 68 percent and 90 percent confidence intervals respectively. Standard errors are clustered by firm and country-time.

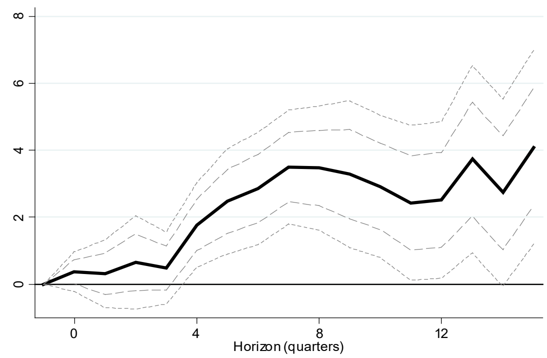
Figure 9: Robustness: Time-Varying Alternative Digitalization Measures

Panel A: ICIO
(Direct digital inputs)

Panel A.1: Contemporaneous

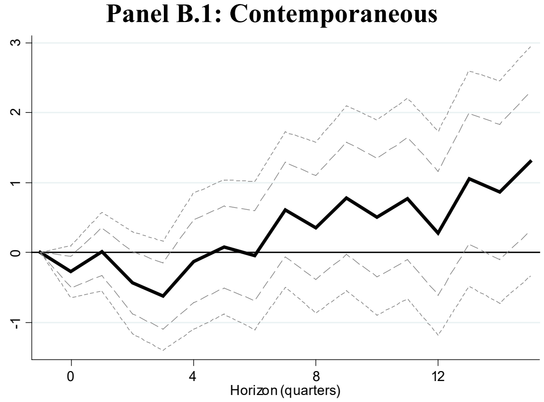


Panel A.2: One-year Lagged

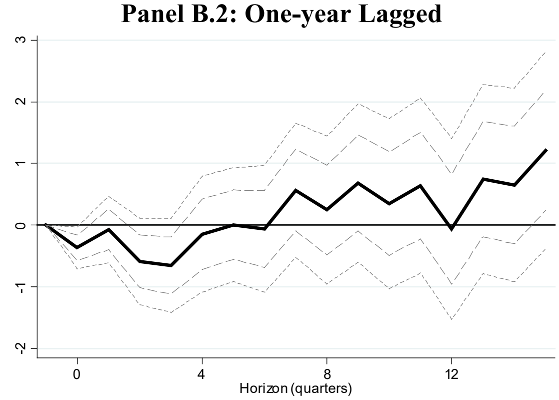


Panel B: TiVA
(Total value added from digital inputs)

Panel B.1: Contemporaneous



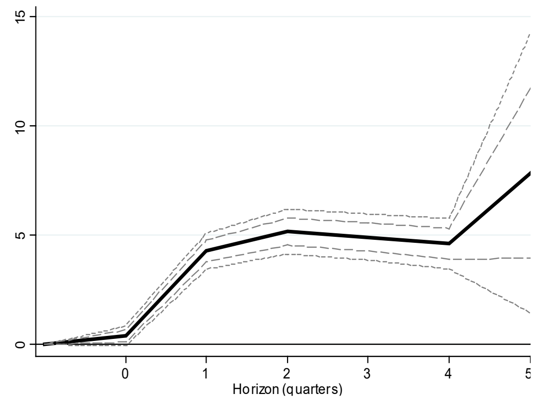
Panel B.2: One-year Lagged



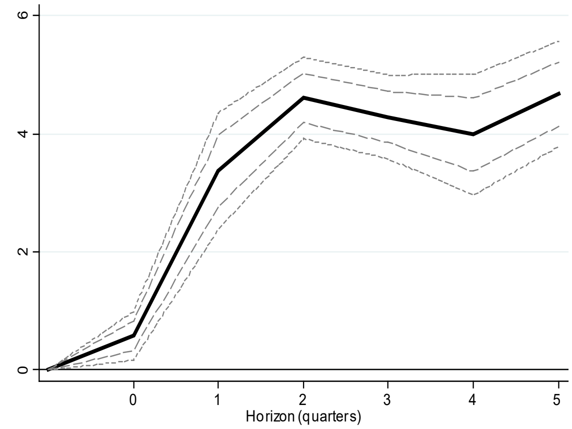
Note: Impulse response function based on local projection methods following Jordà (2005) using firm-level quarterly data from 75 countries for the period 2001Q1 to 2021Q1. Estimates based on the regression $\Delta y_{n,i,t+k} = \alpha_{ist}^{k} + \gamma_{nq}^{k} + \sum_{j=-k}^{4} \mu_j^k R_{i,t-j} * D^m + \sum_{j=1}^{4} \theta_j^k \Delta y_{n,i,t-j} + \varepsilon_{n,i,t}^{k}$ for different horizons k, where $\Delta y_{n,i,t+k}$ is the log change in revenue of firm n in country i at time t over the next k quarters, $R_{\mathrm{i},t}$ is a dummy which takes value 1 at the start of a technical recession, $D^m \in \{D_{r,i,t}^{ICIO}, D_{r,i,t}^{TiVA}, D_{r,i,t-1}^{ICIO}, D_{r,i,t-1}^{TiVA}\}$ is the standardized value of an alternative country-industry-time-varying measure of digitalization, α_{nq}^{k} are firm-quarter fixed effects, and α_{ist}^{k} are country-sector-time fixed effects. The regression is estimated separately for different horizons k over a four-year period. The solid line shows the point estimate for μ^k for different horizons k, while the dashed and dotted lines are the 68 percent and 90 percent confidence intervals respectively. Standard errors are clustered by firm and country-time.

Figure 10: COVID-19 robustness: Country-Industry Alternative Digitalization Measures

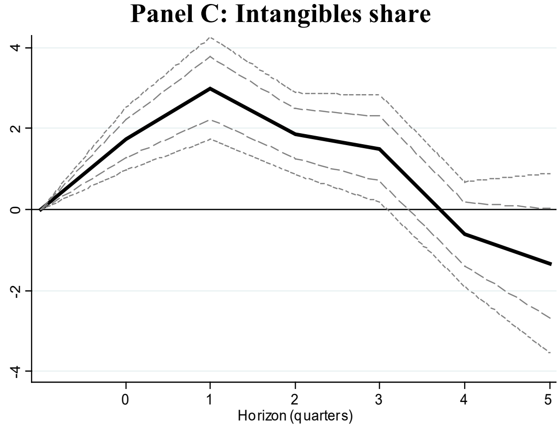
Panel A: ICIO (Direct digital inputs)



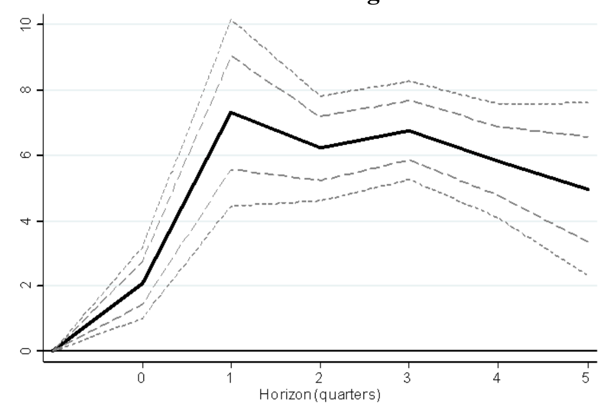
Panel B: TiVA (Total value added from digital inputs)



Panel C: Intangibles share



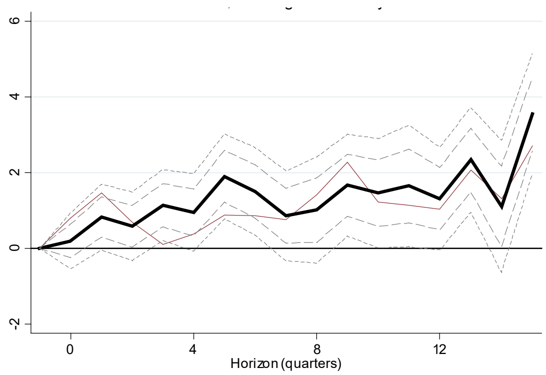
Panel D: LinkedIn Digital Skills



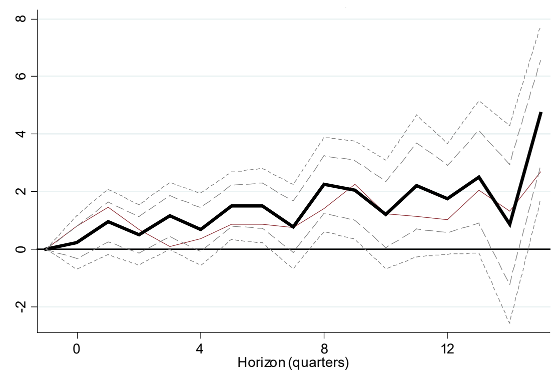
Note: Impulse response function based on local projection methods following Jordà (2005) using firm-level quarterly data from 75 countries for the period 2016Q1 to 2021Q1. Estimates based on the regression $\Delta y_{n,i,t+k} = \alpha_{ist}^k + \gamma_{nq}^k + \sum_{j=-k}^{4} \mu_j^k R_{i,t-j} * D^m + \sum_{j=1}^{4} \theta_j^k \Delta y_{n,i,t-j} + \varepsilon_{n,i,t}^k$ for different horizons k, where $\Delta y_{n,i,t+k}$ is the log change in revenue of firm n in country i at time t over the next k quarters, $R_{i,t}$ is a dummy which takes value 1 at the start of a technical recession from 2019Q4 onwards, $D^m \in \{D_{r,i}^{ICIO}, D_{r,i}^{TiVA}, D_{r,i}^{Int}, D_{r,i}^{TechSkills}\}$ is the standardized value of an alternative country-industry-level measure of digitalization, α_{nq}^k are firm-quarter fixed effects, and α_{ist}^k are country-sector-time fixed effects. The regression is estimated separately for different horizons k over a five-quarter period. The solid line shows the point estimate for μ^k for different horizons k, while the dashed and dotted lines are the 68 percent and 90 percent confidence intervals respectively. Standard errors are clustered by firm and country-time.

Figure 11: Robustness: Alternative Recession Measures

Panel A: Start of Banking and Currency Crises



Panel B: Start of Currency Crises



Note: Impulse response function based on local projection methods following Jordà (2005) using firm-level quarterly data from 75 countries for the period 2001Q1 to 2021Q1. Estimates based on the regression $\Delta y_{n,i,t+k} = \alpha_{ist}^{k} + \gamma_{nq}^{k} + \sum_{j=-k}^{4} \mu_j^k R_{i,t-j} * D^m + \sum_{j=1}^{4} \theta_j^k \Delta y_{n,i,t-j} + \varepsilon_{n,i,t}^{k}$ for different horizons k, where $\Delta y_{n,i,t+k}$ is the log change in revenue of firm n in country i at time t over the next k quarters, $R_{\mathrm{i},t}$ is a dummy which takes value 1 at the start of a banking and/or currency crisis, $D^m = D_r^C$ is the standardized value of the Calvino et al. (2018) measure of industry-wise digitalization, α_{nq}^{k} are firm-quarter fixed effects, and α_{ist}^{k} are country-sector-time fixed effects. The regression is estimated separately for different horizons k over a four-year period. The solid line shows the point estimate for μ^k for different horizons k, while the dashed and dotted lines are the 68 percent and 90 percent confidence intervals respectively. Standard errors are clustered by firm and country-time.

ANNEX 1: DATA

Table A1.1. Sample of 75 Countries by Region

Africa – AFR (3)
Botswana
Mauritius
South Africa

Middle East and Central Asia – MCD (11)
Bahrain
Egypt
Jordan
Kazakhstan
Kuwait
Oman
Pakistan
Qatar
Saudi Arabia
Tunisia
United Arab Emirates

Western Hemisphere –WHD (10)
Argentina
Brazil
Canada
Chile
Colombia
Jamaica
Mexico
Peru
Trinidad & Tobago
United States

Asia & Pacific – APD (17)
Australia
Bangladesh
China
Hong Kong
India
Indonesia
Japan
Macau
Malaysia
New Zealand
Philippines
Singapore
South Korea
Sri Lanka
Taiwan
Thailand
Vietnam

Europe – EUR (34)	
Austria	Lithuania
Belgium	Luxembourg
Bulgaria	Malta
Croatia	Netherlands
Cyprus	Norway
Czech Republic	Poland
Estonia	Portugal
Finland	Romania
France	Russia
Germany	Serbia
Greece	Slovakia
Hungary	Spain
Iceland	Sweden
Ireland	Switzerland
Israel	Turkey
Italy	Ukraine
Latvia	United Kingdom

Table A1.2. Number of Firms and Observations by Country

Country	Number of firms	Obs.
United States	4,740	388,680
China	4,077	334,314
Japan	3,085	252,970
India	2,672	219,104
Canada	2,213	181,466
South Korea	1,747	143,254
Taiwan	1,693	138,826
Australia	1,356	111,192
Hong Kong	1,106	90,692
United Kingdom	870	71,340
Malaysia	771	63,222
Thailand	555	45,510
Sweden	525	43,050
Poland	522	42,804
Singapore	471	38,622
France	467	38,294
Germany	450	36,900
Vietnam	412	33,784
Indonesia	399	32,718
Israel	322	26,404
Pakistan	321	26,322
Turkey	280	22,960
Brazil	246	20,172
Italy	220	18,040
Sri Lanka	183	15,006
Bangladesh	178	14,596
South Africa	178	14,596
Russia	177	14,514
Switzerland	168	13,776
Philippines	157	12,874
Greece	155	12,710
Egypt	134	10,988
Norway	129	10,578
Chile	128	10,496
Spain	119	9,758
Finland	117	9,594
Saudi Arabia	114	9,348

Table A1.2, continued. Number of Firms and Observations by Country

Country	Number of firms	Obs.
Netherlands	105	8,610
New Zealand	105	8,610
Mexico	98	8,036
Peru	87	7,134
Jordan	83	6,806
Belgium	75	6,150
Ireland	71	5,822
Oman	71	5,822
Argentina	65	5,330
Romania	63	5,166
Kuwait	61	5,002
Croatia	57	4,674
Bulgaria	54	4,428
Colombia	49	4,018
Austria	45	3,690
Cyprus	45	3,690
United Arab Emirates	45	3,690
Mauritius	44	3,608
Luxembourg	39	3,198
Jamaica	37	3,034
Portugal	36	2,952
Tunisia	27	2,214
Lithuania	23	1,886
Qatar	21	1,722
Malta	20	1,640
Hungary	18	1,476
Bahrain	17	1,394
Kazakhstan	15	1,230
Estonia	14	1,148
Iceland	14	1,148
Latvia	14	1,148
Trinidad & Tobago	14	1,148
Serbia	12	984
Ukraine	11	902
Macau	10	820
Botswana	7	574
Czech Republic	6	492
Slovakia	6	492

Table A1.3. Number of Firms and Observations by Sector

Sector	Number of Firms	Obs.
Materials	5,433	445,506
Capital Goods	4,888	400,816
Technology Hardware and Equipment	2,286	187,452
Consumer Durables and Apparel	2,032	166,624
Software and Services	2,027	166,214
Pharmaceuticals and Biotechnology	1,833	150,306
Food, Beverage and Tobacco	1,800	147,600
Energy	1,714	140,548
Media and Entertainment	1,398	114,636
Consumer Services	1,315	107,830
Retailing	1,291	105,862
Health Care Equipment and Services	1,287	105,534
Professional Services	1,160	95,120
Transportation	933	76,506
Automobiles and Components	865	70,930
Utilities	854	70,028
Semiconductors	774	63,468
Telecommunication Services	407	33,374
Food and Staples Retailing	383	31,406
Household and Personal Products	361	29,602

Table A1.4. Summary Statistics by Revenue

Variable	Count	Mean	Std	25th	75th
Revenue	1,692,161	5.49	3.58	3.39	7.8
Revenue – High Digital (above 75^{th} percentile)	264,067	5.26	3.78	2.84	7.81

Table A1.5. Recession Variables Summary Statistics

Variable	Source	Countries	Coverage	Obs.	Mean	Std	Min	Max
Start of Technical Recession	Haver Analytics and World Economic Outlook	106	1960Q2-2022Q4	12,011	0.05	0.21	0	1
Currency crises (converted to quarterly)	Reinhart and Rogoff (2009)	63	1960q2-2014q4	7,230	0.06	0.20	0	1
Banking and currency crises (converted to quarterly)	Reinhart and Rogoff (2009)	63	1960q2-2014q4	7,230	0.08	0.27	0	1

Table A1.6. Descriptive Statistics of Digitalization variables

Variable	Source	Countries	Obs.	Mean	Std	Min	Max
Calvino et al. (2018)	Calvino et al. (2018)	76	3,304,900	.60	.26	.25	1
ICIO	OECD Inter-Country Input-Output Tables (OECD 2021b)	56	2,861,280	.11	.20	0	.86
TiVA	OECD Trade in Value Added database (OECD 2021c)	58	2,016,718	.083	.15	0	.76
Intangibles	Capital IQ	76	1,301,928	.11	.17	0	.76
Tech Skills	LinkedIn	38	2,254,000	.099	.04	0	.19

Table A1.7. Rank of most digital sectors by digitalization measure

Most/Least Digital	Calvino	ICIO	TIVA	Intangibles	LinkedIn Digital Skills
1	Wireless Telecommunication Services	Semiconductors and Semiconductor Equipment	IT Services	Health Care Technology	Communications Equipment
2	Industrial Conglomerates	Technology Hardware, Storage and Peripherals	Interactive Media and Services	Wireless Telecommunication Services	Software
3	Auto Components	Electronic Equipment, Instruments and Components	Health Care Equipment and Supplies	Interactive Media and Services	Electronic Equipment, Instruments and Components
N – 2	Building Products	Textiles, Apparel and Luxury Goods	Road and Rail	Textiles, Apparel and Luxury Goods	Electric Utilities
N – 1	Water Utilities	Food Products	Diversified Consumer Services	Construction and Engineering	Water Utilities
N = 60	Road and Rail	Oil, Gas and Consumable Fuels	Oil, Gas and Consumable Fuels	Marine	Paper and Forest Products

Table A1.8. Variation of digitalization measures on country-sector-time fixed effects

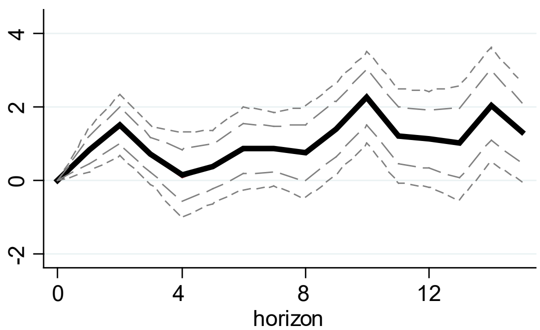
	(1)	(2)	(3)	(4)
	Calvino (industry)	**Intangibles** (country-industry)	**TiVA** (country-industry)	**ICIO** (country-industry)
R-squared from regression on Country-Sector-Time FE	0.024	0.044	0.070	0.021
Observations	2,710,018	2,699,932	2,263,446	2,606,944

Note: R2 obtained from regressing the digitalization measures on our baseline country-sector-time fixed effects. We find that substantial variation remains, implying substantial cross-industry within-sector variation in digitalization (note: 60 industries nested within 20 sectors).

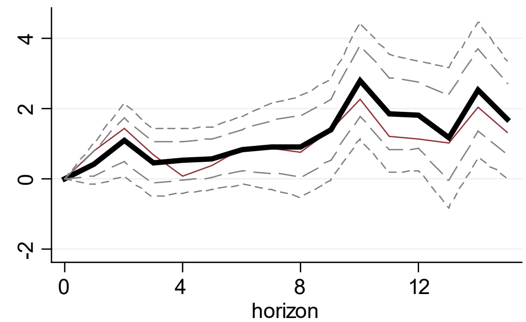
ANNEX 2: ADDITIONAL RESULTS

Figure A2.1: Robustness: Excluding GFC, COVID-19 and Banking Crisis

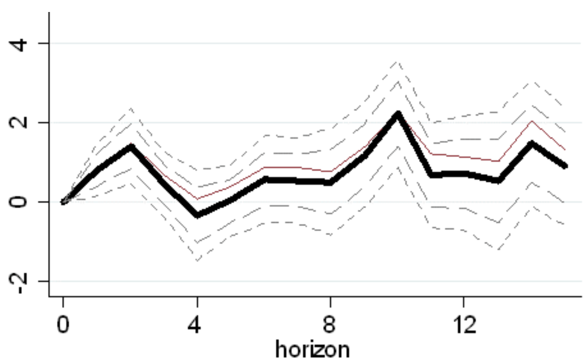
Panel A: Exclude 2020



Panel B: Exclude 2008

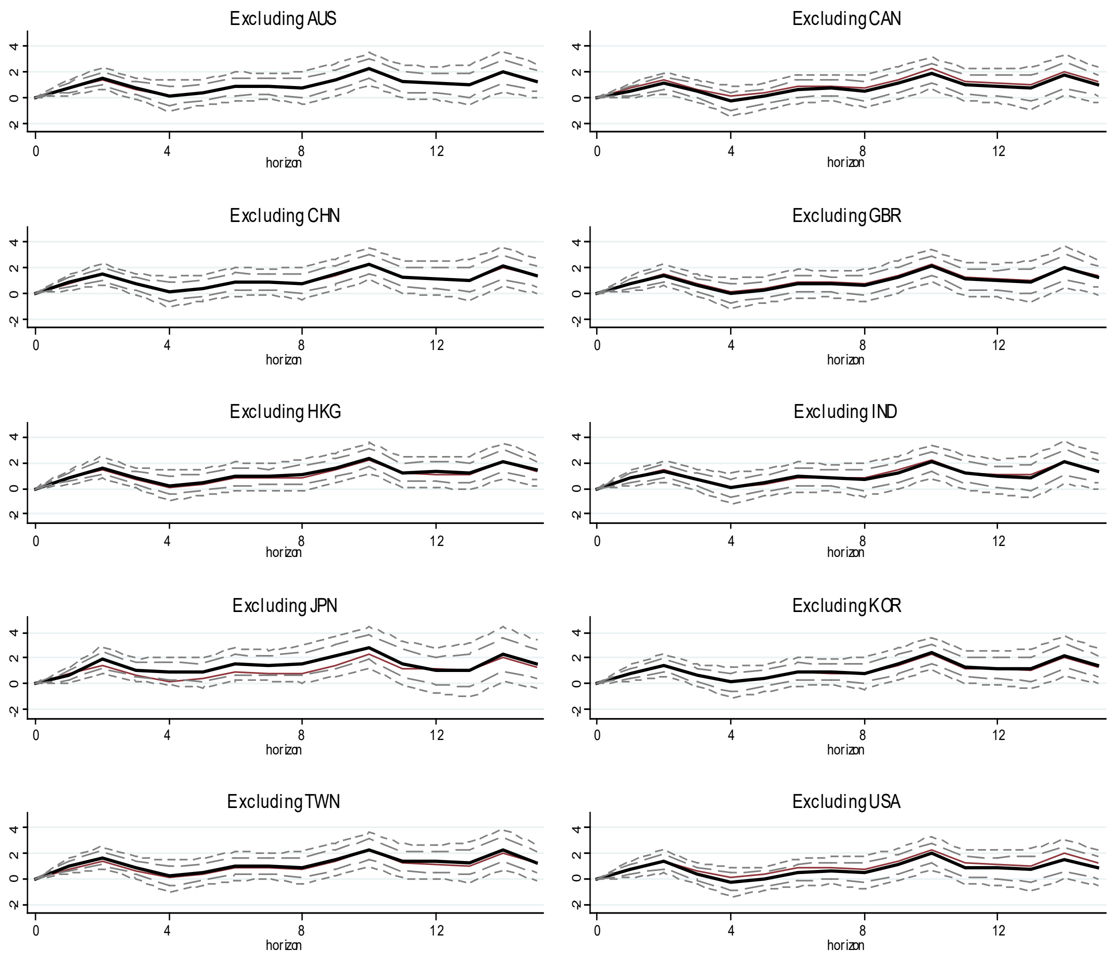


Panel C: Excluding Banking Crisis



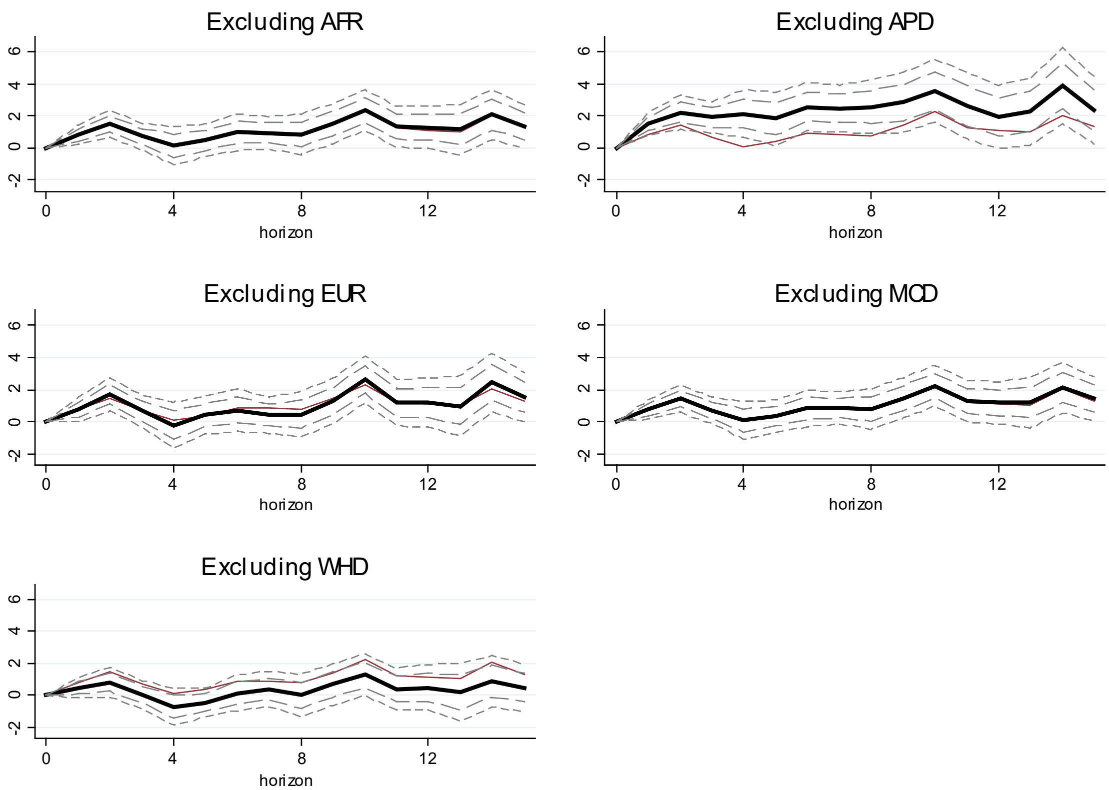
Note: Left top panel excludes the year 2020 from the estimation, top right panel excludes the year 2008 and bottom left panel excludes banking crisis from the sample. Impulse response function based on local projection methods following Jordà (2005) using firm-level quarterly data from 75 countries for the period 2001Q1 to 2021Q1. Estimates based on the regression $\Delta y_{n,i,t+k} = \alpha^k_{ist} + \gamma^k_{nq} + \sum_{j=-k}^{4} \mu^k_j R_{i,t-j} * D^m + \sum_{j=1}^{4} \theta^k_j \Delta y_{n,i,t-j} + \varepsilon^k_{n,i,t}$ for different horizons k, where $\Delta y_{n,i,t+k}$ is the log change in revenue of firm n in country i at time t over the next k quarters, $R_{\mathrm{i},t}$ is a dummy which takes value 1 at the start of a technical recession, $D^m = D^C_r$ is the standardized value of the Calvino et al. (2018) measure of industry-wise digitalization, α^k_{nq} are firm-quarter fixed effects, and α^k_{ist} are country-sector-time fixed effects. The regression is estimated separately for different horizons k over a four-year period. The solid line shows the point estimate for μ^k for different horizons k, while the dashed and dotted lines are the 68 percent and 90 percent confidence intervals respectively. Standard errors are clustered by firm and country-time.

Figure A2.2: Robustness: Excluding Countries with Most Observations



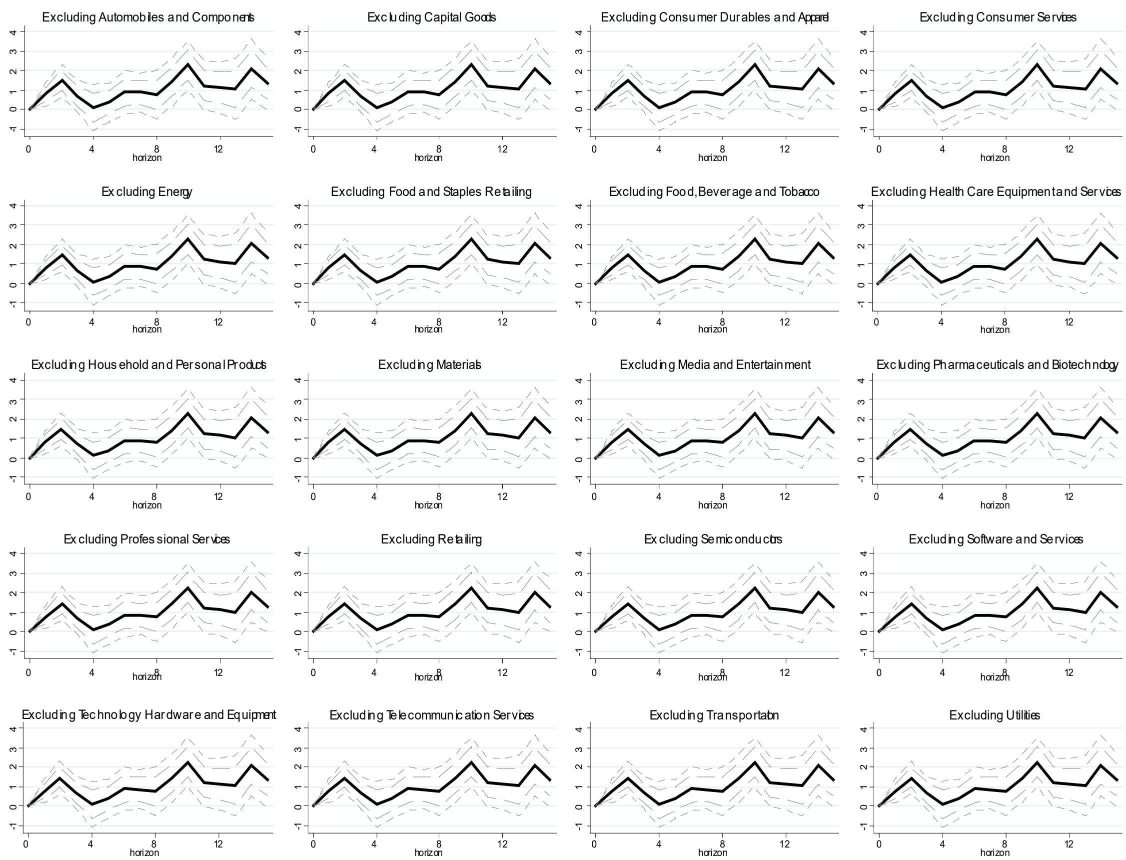
Note: Responses are calculated excluding one country at a time. Impulse response function based on local projection methods following Jordà (2005) using firm-level quarterly data from 75 countries for the period 2001Q1 to 2021Q1. Estimates based on the regression $\Delta y_{n,i,t+k} = \alpha_{ist}^{k} + \gamma_{nq}^{k} + \sum_{j=-k}^{4} \mu_j^k R_{i,t-j} * D^m + \sum_{j=1}^{4} \theta_j^k \Delta y_{n,i,t-j} + \varepsilon_{n,i,t}^{k}$ for different horizons k, where $\Delta y_{n,i,t+k}$ is the log change in revenue of firm n in country i at time t over the next k quarters, $R_{\mathrm{i},t}$ is a dummy which takes value 1 at the start of a technical recession, $D^m = D_r^C$ is the standardized value of the Calvino et al. (2018) measure of industry-wise digitalization, α_{nq}^{k} are firm-quarter fixed effects, and α_{ist}^{k} are country-sector-time fixed effects. The regression is estimated separately for different horizons k over a four-year period. The solid line shows the point estimate for μ^k for different horizons k, while the dashed and dotted lines are the 68 percent and 90 percent confidence intervals respectively. Standard errors are clustered by firm and country-time.

Figure A2.3: Robustness: Excluding One Region at a Time



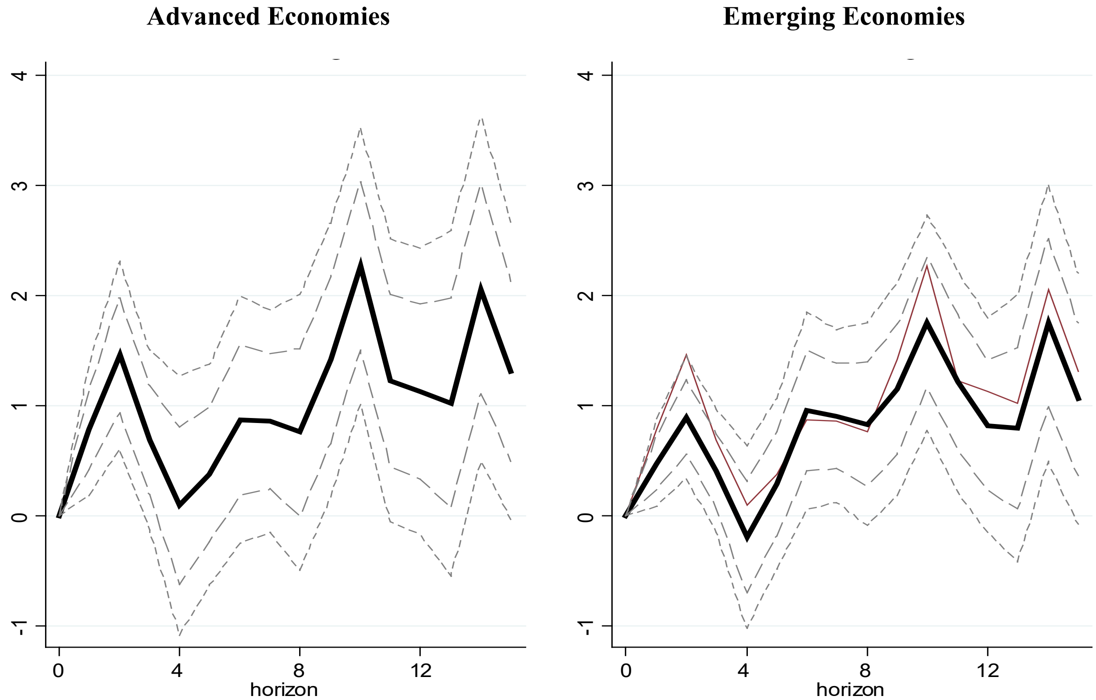
Note: Responses are calculated excluding one region at a time. Impulse response function based on local projection methods following Jordà (2005) using firm-level quarterly data from 75 countries for the period 2001Q1 to 2021Q1. Estimates based on the regression $\Delta y_{n,i,t+k} = \alpha_{ist}^{k} + \gamma_{nq}^{k} + \sum_{j=-k}^{4} \mu_j^k R_{i,t-j} * D^m + \sum_{j=1}^{4} \theta_j^k \Delta y_{n,i,t-j} + \varepsilon_{n,i,t}^{k}$ for different horizons k, where $\Delta y_{n,i,t+k}$ is the log change in revenue of firm n in country i at time t over the next k quarters, $R_{\mathrm{i},t}$ is a dummy which takes value 1 at the start of a technical recession, $D^m = D_r^C$ is the standardized value of the Calvino et al. (2018) measure of industry-wise digitalization, α_{nq}^{k} are firm-quarter fixed effects, and α_{ist}^{k} are country-sector-time fixed effects. The regression is estimated separately for different horizons k over a four-year period. The solid line shows the point estimate for μ^k for different horizons k, while the dashed and dotted lines are the 68 percent and 90 percent confidence intervals respectively. Standard errors are clustered by firm and country-time.

Figure A2.4: Robustness: Excluding One Sector at a Time



Note: Responses are calculated excluding one 2-digit sector at a time. Impulse response function based on local projection methods following Jordà (2005) using firm-level quarterly data from 75 countries for the period 2001Q1 to 2021Q1. Estimates based on the regression $\Delta y_{n,i,t+k} = \alpha_{ist}^{k} + \gamma_{nq}^{k} + \sum_{j=-k}^{4} \mu_j^k R_{i,t-j} * D^m + \sum_{j=1}^{4} \theta_j^k \Delta y_{n,i,t-j} + \varepsilon_{n,i,t}^{k}$ for different horizons k, where $\Delta y_{n,i,t+k}$ is the log change in revenue of firm n in country i at time t over the next k quarters, $R_{\mathrm{i},t}$ is a dummy which takes value 1 at the start of a technical recession, $D^m = D_r^C$ is the standardized value of the Calvino et al. (2018) measure of industry-wise digitalization, α_{nq}^{k} are firm-quarter fixed effects, and α_{ist}^{k} are country-sector-time fixed effects. The regression is estimated separately for different horizons k over a four-year period. The solid line shows the point estimate for μ^k for different horizons k, while the dashed and dotted lines are the 68 percent and 90 percent confidence intervals respectively. Standard errors are clustered by firm and country-time.

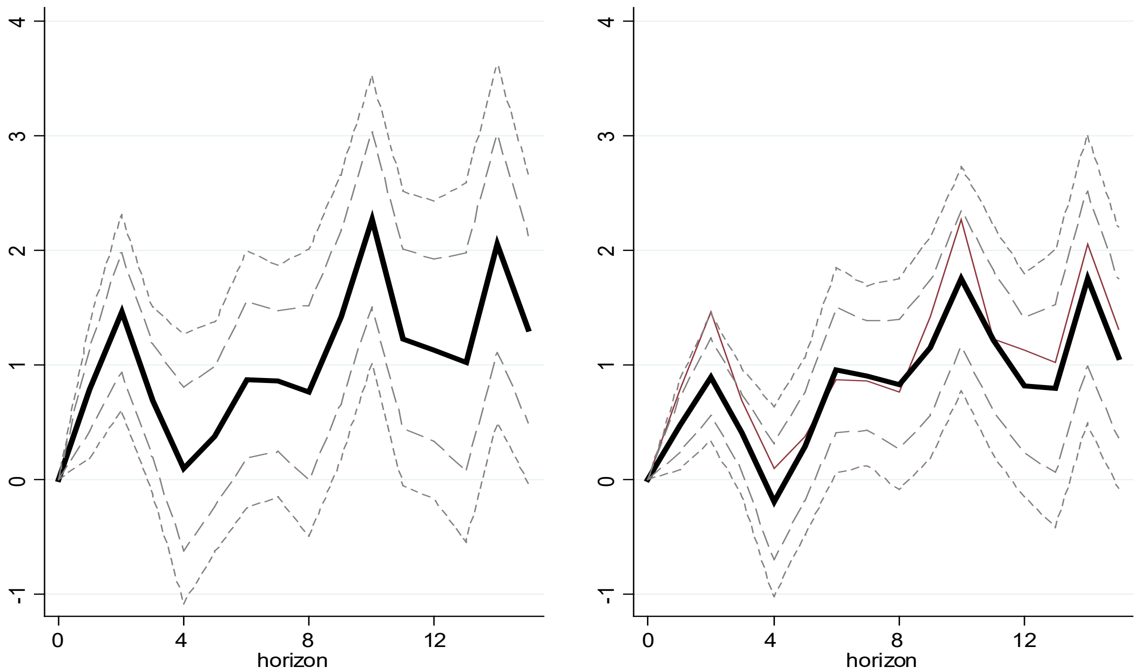
Figure A2.5: Robustness: Country Income Level



Note: Impulse response function based on local projection methods following Jordà (2005) using firm-level quarterly data from 75 countries for the period 2001Q1 to 2021Q1. Estimates based on the regression $\Delta y_{n,i,t+k} = \alpha_{ist}^{k} + \gamma_{nq}^{k} + \sum_{j=-k}^{4} \mu_j^k R_{i,t-j} * D^m + \sum_{j=1}^{4} \theta_j^k \Delta y_{n,i,t-j} + \varepsilon_{n,i,t}^{k}$ for different horizons k, where $\Delta y_{n,i,t+k}$ is the log change in revenue of firm n in country i at time t over the next k quarters, $R_{\mathrm{i},t}$ is a dummy which takes value 1 at the start of a technical recession, $D^m = D_r^C$ is the standardized value of the Calvino et al. (2018) measure of industry-wise digitalization, α_{nq}^{k} are firm-quarter fixed effects, and α_{ist}^{k} are country-sector-time fixed effects. The regression is estimated separately for different horizons k over a four-year period. The solid line shows the point estimate for μ^k for different horizons k, while the dashed and dotted lines are the 68 percent and 90 percent confidence intervals respectively. Standard errors are clustered by firm and country-time. The red line shows the baseline effect using the full sample.

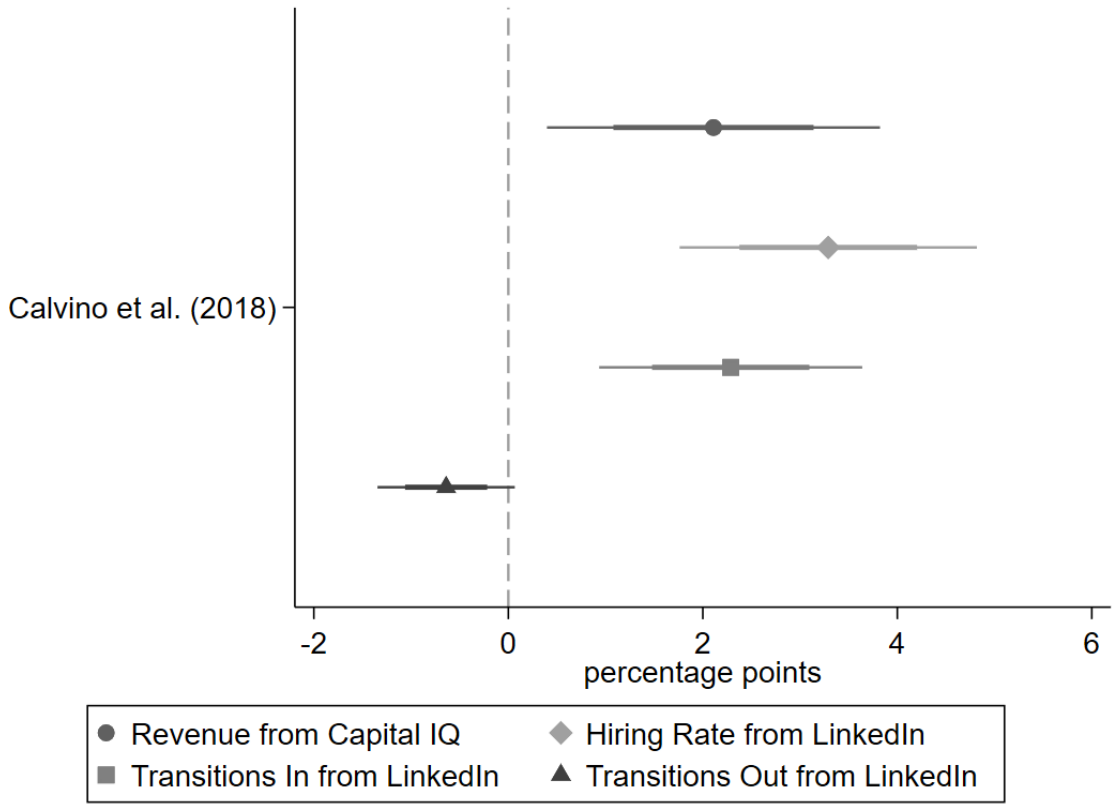
Figure A2.6: Robustness: Different winsorization thresholds

Winsorizing 0.5 percent | **Winsorizing 5 percent**



Note: Impulse response function based on local projection methods following Jordà (2005) using firm-level quarterly data from 75 countries for the period 2001Q1 to 2021Q1. Estimates based on the regression $\Delta y_{n,i,t+k} = \alpha_{ist}^{k} + \gamma_{nq}^{k} + \sum_{j=-k}^{4} \mu_j^k R_{i,t-j} * D^m + \sum_{j=1}^{4} \theta_j^k \Delta y_{n,i,t-j} + \varepsilon_{n,i,t}^{k}$ for different horizons k, where $\Delta y_{n,i,t+k}$ is the log change in revenue of firm n in country i at time t over the next k quarters, $R_{\mathrm{i},t}$ is a dummy which takes value 1 at the start of a technical recession, $D^m = D_r^C$ is the standardized value of the Calvino et al. (2018) measure of industry-wise digitalization, α_{nq}^{k} are firm-quarter fixed effects, and α_{ist}^{k} are country-sector-time fixed effects. The regression is estimated separately for different horizons k over a four-year period. The solid line shows the point estimate for μ^k for different horizons k, while the dashed and dotted lines are the 68 percent and 90 percent confidence intervals respectively. Standard errors are clustered by firm and country-time. The red line shows the baseline effect using the full sample.

Figure A2.7: Robustness: Estimations using alternative specification



Note: This figure shows the results from estimating the impacts of digitalization using the alternative methodology of Duval et al. (2020). The top coefficient plotted is estimated from Capital IQ firm data in a regression of the form $\Delta y_{n,i} = \alpha_i + \alpha_s + \mu * D_r^C + \epsilon_{n,i}$, where $\Delta y_{n,i}$ is the change in log average quarterly revenue after vs. before the pandemic for firm n in country i, α_i and α_s are country and sector fixed effects, and D_r^C is the Calvino et al. (2018) digitalization measure. The other three coefficients are estimated from industry-level LinkedIn data in a regression of the form $\Delta y_{r,i} = \alpha_i + \mu * D_r^C + \epsilon_{r,i}$, where $y_{r,i}$ is now the log of average hiring rates or transitions into or out of the industry. Each coefficient therefore reflects the percentage point impact on growth in revenue, hiring, transitions in or transitions out that is associated with belonging to an industry that is one standard deviation more digitalized than the average. The thick and thin confidence spikes show the 68 percent and 90 percent confidence intervals respectively. Standard errors are clustered by country.

PUBLICATIONS

Digitalization and Resilience

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