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Digitalization and resilience☆

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ABSTRACT

This paper investigates the role of digitalization 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.

1. Introduction

The COVID-19 pandemic is expected to cause significant scarring—that is, persistent output losses. According to the IMF's latest projections, global GDP levels for 2024 are approximately 5.3 % 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 digitalization improve economic resilience by mitigating such scarring? In principle, yes. Firms and industries harnessing digital technologies can unlock productivity gains and improve their connection to distant customers and employees. Digitalization can support sales through both price and quantity channels: automation and other productivity gains could allow firms to undercut competitors, while remote work and contactless online payments could reduce the impact of shocks on connections to workers and consumers.[2] Moreover, digitalization supports the ability to work remotely or sell without contact, capabilities that have shielded workers and firms from the pandemic's negative effects. Nonetheless, digitalization can also displace some workers and require significant adjustment costs. Simple correlations suggest a positive and potentially important role: estimates of output losses during the pandemic are higher in countries with weaker digital infrastructure (Fig. 1), and the number of job posts fell less and recovered more quickly in digital occupations (Fig. 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. Our baseline measure of digitalization is the industry-wise rating of Calvino et al.

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[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.

[2] For instance, Jaumotte et al. (2023) find that during the COVID-19 pandemic higher digitalization levels shielded both productivity and hours worked.

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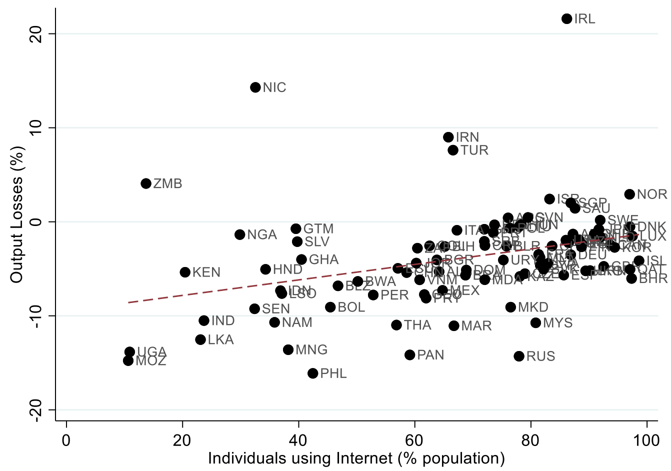


Fig. 1. Scarring and internet access (percent).
Notes: Output losses are computed as the percent deviation between pre-pandemic (January 2020) and latest GDP projections for 2024. Negative values reflect underperformance relative to pre-pandemic expectations; the few cases of positive values reflect overperformance.
Source: World Economic Outlook and World Bank Development Indicators.

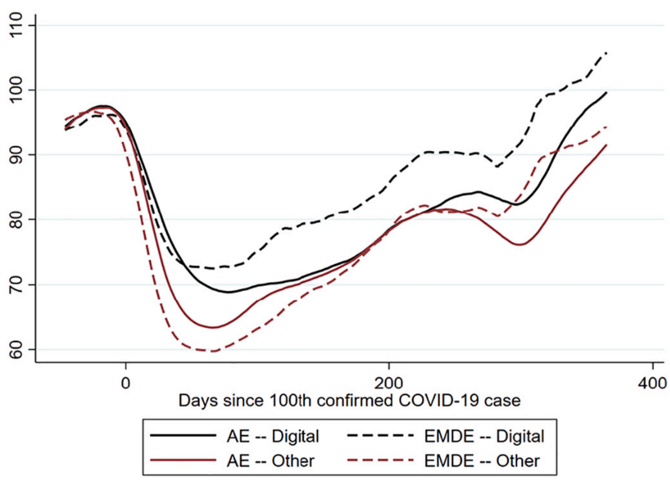


Fig. 2. Job posts by income group (30-day MA, indexed to January + February 2020).
Sample contains daily job counts of total job posts for 35 countries. AE = Advanced Economies; EMDE = Emerging Market and Developing Economies.
Source: Indeed.com and authors' calculations.

(2018), who construct digitalization quartiles using Information and Communication Technology (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.[3]

Our results suggest that digitalization significantly reduces sales losses. 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 % lower sales 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, to reduce endogeneity, we focus on pre-determined and time-invariant measures of digitalization, but some recessions could induce firms to become more digital.[4] This would imply 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 importance of remote work and contactless sales. Accordingly, when we focus on the pandemic period, early data suggest an even larger mitigation effect of digitalization: we find that one year after the COVID-19 recession, firms in industries that are one standard deviation more digitalized than the mean already experience about 4 % smaller declines in sales than other firms—which is two times what we find using the full sample.

The 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 licensing agreements—the fact that our findings are robust across this wide range of measures affirms that digitalization can contribute to strengthening economic resilience at the firm level.

1.1. 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. Hershbein and Kahn (2018) and Jaimovich and Siu (2020), among others, assess the relationship between recessions and technology prior to the pandemic. Since the pandemic, Alcedo et al. (2022) trace the rise in e-commerce, Bellatin et al. (2023) find that the share of adverts for jobs producing digital technologies increased in response to lockdowns, and Oikonomou et al. (2023) find that unemployment rose less in US states with greater IT adoption pre-pandemic. Comin et al. (2022) use data from three emerging market countries (Brazil, Senegal and Vietnam) to examine the impact of pre-pandemic technological sophistication on firms' sales during the pandemic, and also find a positive impact.[5] We build on Lim and Morris (2023) who assess the impact of broader innovation on firm profitability during the pandemic, and our paper also relates to Paunov (2012) and Armand and Mendi (2018) who consider the reverse relationship, namely the impact of downturns on innovation. 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 Middle East and Central Asia 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

[3] 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.

[4] While we observe that even relatively less digital industries and firms increased digital adoption during the pandemic, the evidence from historical recessions is not clear cut. We used the time-varying measures of digitization that we construct in the paper to investigate whether more digital industries further increased their degree of digitalization after recessions. Following our baseline specification, we regressed the time-varying measures on the interaction of recessions with the non-time-varying measures. The results are mixed and do not provide conclusive evidence that digitalization itself increases following recessions.

[5] See also Jaumotte et al. (2023) who provide an overview of the productivity and labor market implications of digitalization in advanced economies during the pandemic.

aftermath of various types of recessions, both before and during the pandemic, for a larger set of countries and firms, and across a wide range of digitalization measures.

The rest of the paper is organized as follows. Section 2 presents the data and Section 3 outlines our methodology. Section 4 presents our results, first from recessions over the last twenty years and then on the initial impact of the COVID-19 pandemic. Section 5 presents an extensive list of robustness checks, and Section 6 concludes.

2. Data

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

2.1. 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, making it particularly suitable for the analysis of business cycles. It covers a large, unbalanced sample of 150 countries from 1950Q1 to 2021Q2. To reduce significant gaps in the time series, we restrict the sample to 2001Q1 onwards, which 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 Appendix 1. We also conducted some data cleaning to ensure its accuracy and relevance. 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 account for outliers.

2.2. Recessions and other macroeconomic data

Our baseline measure for recessions is the start of a technical recession, defined by two or more 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. Then, we define a dummy where the first observation in each recession episode in each country is set to one, and all other observations are set to zero. 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 from Reinhart and Rogoff (2009). Recession data summary statistics are reported in Table A1.5.

2.3. 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^C_r 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.[6] 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, while we use the version based on data in 2013–15—the most recent available period—Calvino et al. (2018) find that only 17 % of sectors would change their relative digitalization quartile, if it were recalculated separately in the earliest available period, 2001–03. 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 $D^{ICIO}_{r,i} = \sum_l \alpha_{rli} \cdot D_l$ 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".[7] To construct this measure, we use consolidated data from 66 countries via the OECD Inter-Country Input-Output Tables (OECD, 2021b).[8] 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 $D^{TiVA}_{r,i} = \sum_l \zeta_{rli} \cdot D_l$ where ζ_{rli} is the share of total input value added of industry r country i that comes from industry l.[9] This uses data from the OECD Trade in Value Added database (OECD, 2021c), again for 66 countries. $D^{TiVA}_{r,i}$ therefore repeats $D^{ICIO}_{r,i}$ 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

[6] The primary data sources used by Calvino et al. (2018) are: OECD Annual National Accounts, EU-KLEMS, OECD Structural Analysis (STAN) Database, the International Federation of Robotics, national labor force survey, the OECD Programme for the International Assessment of Adult Competencies (PIAAC), and Eurostat.

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

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

[9] 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.

Table 1
Summary of digitalization measures.

	Notation	Variation	Industry classification[a]
Calvino	D_r^C	Industry	ISIC Rev. 4 (2-digit)
ICIO	$D_{r,i}^{ICIO}$	Country-industry	ISIC Rev. 4 (2-digit)
TIVA	$D_{r,i}^{TiVA}$	Country-industry	ISIC Rev. 4 (2-digit)
Intangibles	$D_{r,i}^{Int}$	Country-industry	Capital IQ custom (2-digit)
Digital Skills	$D_{r,i}^{TechSkills}$	Country-industry	LinkedIn custom (2-digit)

[a] Of the source format. For the regressions we manually map all variables onto the 60 industries in the Capital IQ classification.

Table 2
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

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

digital services. The set of countries used to construct them, however, is still not identical to that for which we have 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.[10] 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:

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

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.[11] Digitalization measures summary statistics are reported in Table A1.6.

Table 1 summarizes the various measures of digitalization, and Table 2 shows the cross-correlations between them. 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.[12] 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.[13]

Table A1.8 shows descriptive statistics across groups defined by our baseline digitalization measure and highlights that there are not substantial differences on firm observables. The distributions of firm size, revenue, return on assets, firm age and interest coverage ratio are similar across levels of digitalization. The largest difference across groups is on profitability, where firms in more digital industries are on average *less* profitable—which, if anything, counts against us finding that they are more resilient through recessions, as they have less retained earnings to continue investing through downturns.

3. 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) impact of recessions on firm revenue using the following specification:

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

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 Eq. (1) to estimate how the dynamic effect of recessions on revenues varies across firms depending on the extent of industry digitalization. We estimate the following specification:

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

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.,

[10] 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 75 %) that do not report intangibles data in their balance sheets.

[11] 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.

[12] For instance, the LinkedIn measure is highly correlated with the other measures and ranks similar industries as being most and least digitalized. This reassures us that our results are not driven by biases specific to any one measure, such as variation in LinkedIn penetration across countries. Fig. A1.1 in the Appendix shows that the measures also provide similar rankings across regions.

[13] Fig. A1.2 in Appendix plots the trend in the average value of each of our time-varying digitalization measures, highlighting the acceleration in digitalization over our sample period.

changes in national policies to support a particular sector).[14] 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.[15] We therefore drop the country-sector-time 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 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.

We also consider broader outcome measures for the pandemic recessions, to compensate for the shorter post-recession window over which we can observe revenue responses. We again utilize high-frequency cross-country data from LinkedIn profiles, in this case industry-wise hiring and worker transitions.[16] To do so we convert our main specification to the industry level, and estimate:

$$\Delta y_{r,i,t+k} = \alpha_{it}^k + \alpha_{ri}^k + \sum\nolimits_{j=-k}^{4} \mu_j^k R_{i,t-j} {}^{*} D^m + \sum\nolimits_{j=1}^{4} \theta_j^k \Delta y_{r,i,t-k} + \epsilon_{r,i,t} \quad \forall k = 0, 1 \ldots 15 \tag{3}$$

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.

4. 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.

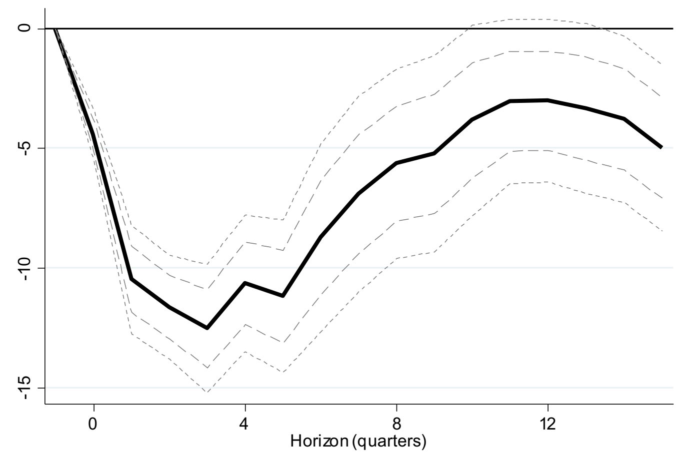


Fig. 3. Unconditional effect of recessions on changes in (log) revenue.
Notes: Impulse response function based on local projection methods following Jordà (2005) using firm-level quarterly data from 75 countries for the period 2001Q1 to 2021Q1. Estimates based on the regression $\Delta y_{n,i,t+k} = \alpha_{is}^k + \gamma_{nq}^k + \sum_{j=-k}^4 \mu_j^k R_{i,t-j} + \sum_{j=1}^4 \theta_j^k \Delta y_{n,i,t-j} + \varepsilon_{n,i,t}^k$ 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 % and 90 % confidence intervals respectively. Standard errors are clustered by firm and country-time.

4.1. Historical recessions

Fig. 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 % 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 % four quarters after the recession and by 5 % after 8 quarters.

Fig. 4 is analogous to Fig. 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 % lower revenue losses after two years. The difference is larger (about 2 %) 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.[17] Since we include country-sector-time fixed effects, this result is not driven by differing characteristics of firms across (broad) sectors, only by within-sector differences across (narrow) industries. Nonetheless, firms in more digitalized industries within a sector may also differ systematically from other firms in the same sector. To address potential omitted variables bias, we augment specification (2) to include, in turn, the interaction between recessions and the following observables: firm size, revenue as a share of assets, profitability, return on assets, age, and interest coverage ratio. The results reported in Fig. 5 confirm our main findings.

[14] 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 A1.9 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.

[15] Specifically, 5 countries have pandemic recessions beginning after 2020Q1: Austria, France, Saudi Arabia, Ukraine and Venezuela. The full breakdown of COVID-19 recessions is shown in Table A1.10.

[16] The LinkedIn outcome measures (hiring and worker transitions) are particularly well-suited to examining the impact of the pandemic on labor markets because they are both high frequency and comparable across countries, unlike country-specific labor surveys.

[17] These results can also be characterized in terms of ex-ante resilience—the extent to which digitalization mitigates the initial negative impact of recession—and ex-post resilience—the extent to which digitalization facilitates a faster recovery after the event. Fig. 4 shows that digitalization had a significant positive impact at horizons zero and one, indicative of higher ex-ante resilience, but also a substantial positive impact over the subsequent years, indicative of higher ex-post resilience.

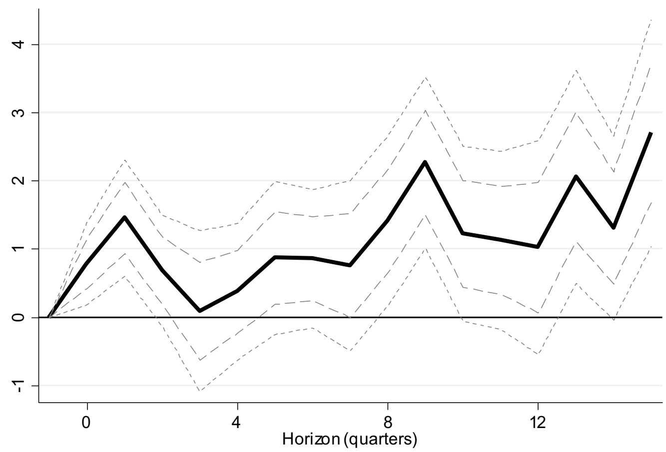


Fig. 4. Differential effect of recession on log revenue for highly digitalized industries vs. average.

Notes: 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, $R_{i,t}$ 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 % and 90 % confidence intervals respectively. Standard errors are clustered by firm and country-time.

Along with Table A1.8 in the Appendix, which shows that firms in more vs. less digitalized industries do not differ substantially on observables, this analysis provides initial reassurance that our results are not driven by differences in the structure of digitalized firms. We discuss further robustness checks in Section 5.

4.2. 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, especially by facilitating remote work and contact-less 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 that began on or after 2019Q4.[18] We also restrict the overall sample to 2016Q1 onwards so that our fixed effects are only estimated from a relevant timespan. Fig. 6 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 % after five quarters—a magnitude almost four times that associated with a typical recession, reflecting the severity and the unprecedented nature of the pandemic.

Fig. 7 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 % higher four quarters after a recession and increases to close to 5 % after five quarters. This difference is statistically significant and precisely estimated, and more than four times larger than the corresponding impact of an average historical recession after five quarters. Thus, the data strongly support the idea that digitalization has been especially important during the COVID-19 pandemic recession, given the unprecedented measures introduced to reduce mobility and social contact.[19,20]

This higher revenue growth may also have allowed firms in more digitalized industries to expand relative to other firms. Fig. 8 shows the differential impact 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 % faster than in average industries in the year after the COVID-19 recession, and almost 4 % 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 % faster (1 % slower) than in other industries in the two years after the shock.[21]

5. Robustness checks

This section provides several robustness checks to demonstrate the generality of our results. We provide seven types of checks, focused on: i) alternative digitalization measures, ii) alternative recession definitions, iii) alternative samples, iv) placebo tests, v) additional macroeconomic control variables, vi) additional correlates of digitalization and vii) an alternative methodology.

5.1. 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, 2021a). 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 2.

Fig. 9 shows the differential impact of recessions on revenue growth using digitalization measures defined at the country-industry level. Panel A shows results using $D^{ICIO}_{r,i}$, the share of direct digital inputs, constructed from OECD Inter-Country Input-Output tables (OECD, 2021b). Panel B shows results using $D^{TiVA}_{r,i}$, the digital share of total input value added, constructed from the OECD Trade in Value Added database (OECD, 2021c). Panel C shows results using $D^{Int}_{r,i}$, the average share of

[18] 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 difference-in-differences approach also includes recessions prior to the COVID-19 period. The distribution of these COVID-19 recessions is shown in Table A1.10.

[19] Firms in more digitalized industries are slightly less affected in the first quarter of the recession episode (horizon zero), but not significantly so; the divergence in performance emerges rapidly in the subsequent year. This suggests digitalization during the pandemic could mostly be characterized as supporting ex-post resilience rather than ex-ante resilience.

[20] To check that the finding of a more important role for digitalization during COVID-19 is not driven by a difference in the types of countries experiencing recessions, in Fig. A2.13 we re-run both Figs. 4 and 7 for the sample of only emerging markets. We find that our results are robust to this specification.

[21] Interestingly, job retention schemes implemented by some countries during the pandemic limited this churn, and hence the relative impact of digitalization on worker transitions. Fig. A2.12 shows the differential responses of log outward transitions in firms in highly digitalized industries relative to the average, separately for countries with below- and above-median shares of workers covered by a job retention scheme in May 2020. There is a substantially larger outflow response in countries with lower coverage. (Inflows and hiring rates also see a stronger response in countries with lower coverage, although to a lesser degree.)

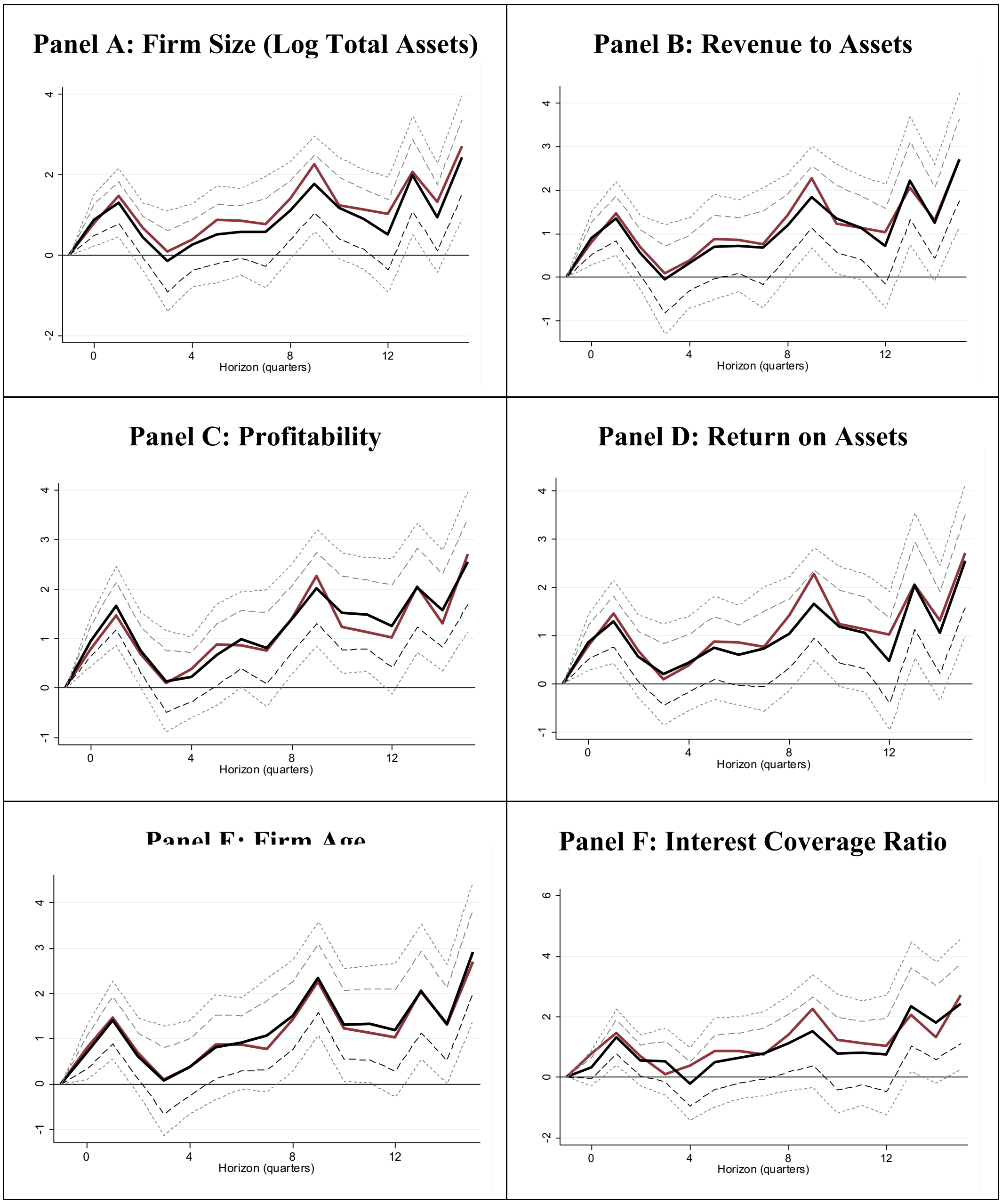


Fig. 5. Differential effect of recession on log revenue for highly digitalized industries vs. average, controlling for differences in firm structure.
Notes: Impulse response function based on local projection methods following Jordà (2005) using firm-level quarterly data from 75 countries for the period 2001Q1 to 2021Q1. Estimates based on the regression $\Delta y_{n,i,t+k} = \alpha^k_{ist} + \gamma^k_{nq} + \sum_{j=-k}^{4} \mu^k_j R_{i,t-j} {}^* D^m + \sum_{j=-k}^{4} \zeta^k_j R_{i,t-j} {}^* C_{n,i,t} + \sum_{j=1}^{4} \theta^k_j \Delta y_{n,i,t-j} + \varepsilon^k_{n,i,t}$ 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, $R_{i,t}$ 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, $C_{n,i,t}$ are the firm-level controls listed in the subtitles, 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 black solid line shows the point estimate for μ^k for different horizons k, while the dashed and dotted lines are the 68 % and 90 % confidence intervals respectively. Standard errors are clustered by firm and country-time. The red line shows the baseline effect using the full sample. Control variables are winsorized at 1 % to account for outliers. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

intangible assets, constructed using Capital IQ balance sheet data. Results are qualitatively robust, with firms in more digital country-industries facing 1–2 % 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. Fig. 10 shows the results, first using the contemporaneous values of $D^{ICIO}_{r,i,t}$ and $D^{TiVA}_{r,i,t}$, then using lagged versions $D^{ICIO}_{r,i,t-1}$ and $D^{TiVA}_{r,i,t-1}$ to mitigate potential endogeneity.[22] Our main findings are qualitatively robust in all cases.

Lastly, we check that our pandemic-specific results also hold when

[22] 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.

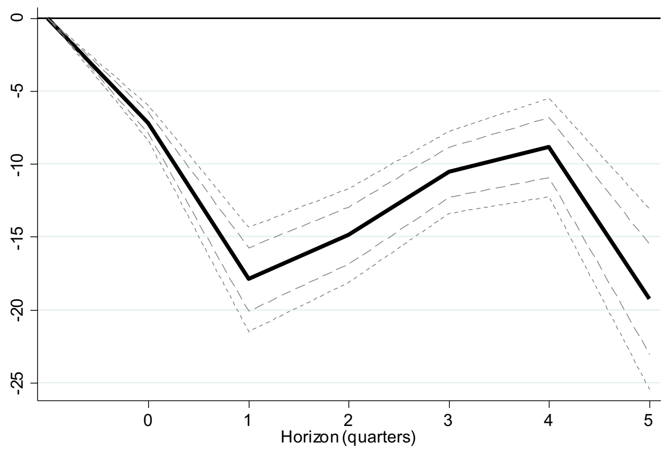


Fig. 6. Unconditional effect of COVID-19 recessions on log revenue.
Notes: Impulse response function based on local projection methods following Jordà (2005) using firm-level quarterly data from 75 countries for the period 2016Q1 to 2021Q1. Estimates based on the regression $\Delta y_{n,i,t+k} = \alpha_{is}^{k} + \gamma_{nq}^{k} + \sum_{j=-k}^{4} \mu_j^k R_{i,t-j} + \sum_{j=1}^{4} \theta_j^k \Delta y_{n,i,t-j} + \varepsilon_{n,i,t}^k$ 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 % and 90 % confidence intervals respectively. Standard errors are clustered by firm and country-time.

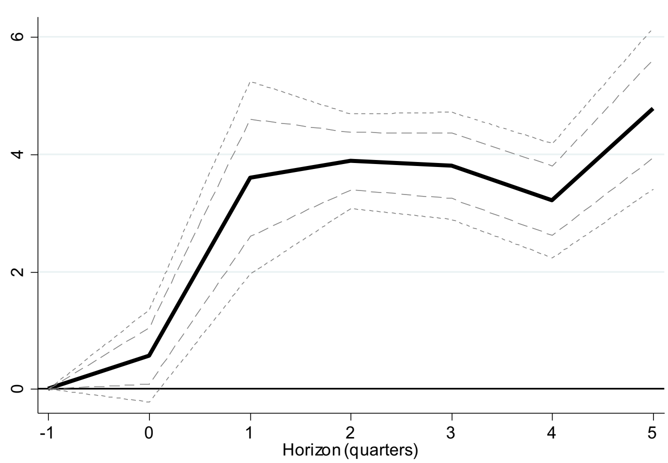


Fig. 7. Differential effect of COVID-19 recession on log revenue for highly digitalized industries vs. average.
Notes: Impulse response function based on local projection methods following Jordà (2005) using firm-level quarterly data from 75 countries for the period 2016Q1 to 2021Q1. Estimates based 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, $D^m = D_r^C$ 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 % and 90 % confidence intervals respectively. Standard errors are clustered by firm and country-time.

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 2. Fig. 11 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.

5.2. 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 (Fig. 12). This similar response to these alternative recessions emphasizes the generality of the role played by digitalization in fostering resilience.

5.3. 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. Fig. A2.1 Panel A in Appendix 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 Fig. 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 Eq. (2) but excluding one country at a time or one region at a time. The results, reported in Figs. A2.2 and A2.3 of Appendix 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 (Fig. A2.4 of Appendix 2).

Fourth, we also check whether the results change depending on countries' income levels. Fig. A2.5 of Appendix 2 shows the differential effect of recessions between highly digitalized firms and the average firm when 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 % 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 (Fig. A2.6).

5.4. Placebo test

We next check the 'parallel trends' assumption, which in our case

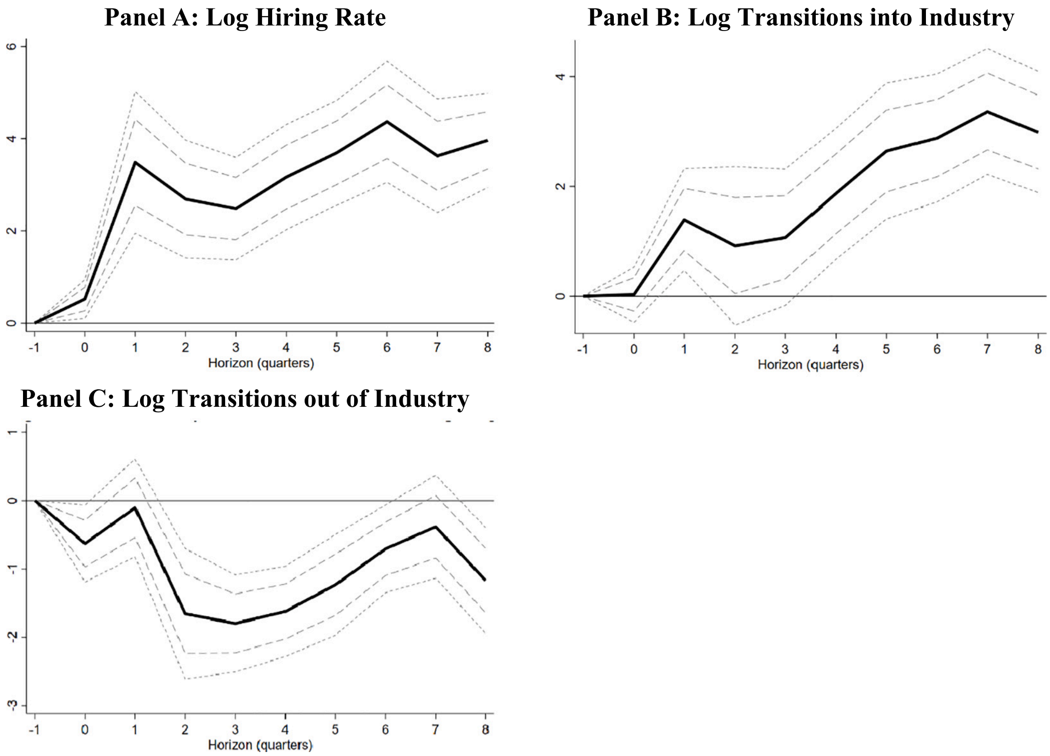


Fig. 8. Differential effect of COVID-19 recession on log hiring rates and workers transition for highly digitalized industries vs. average.
Notes: Impulse response function based on local projection methods following Jordà (2005) using industry-level quarterly data from 40 countries for the period 2016Q1 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, $R_{i,t}$ 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 % and 90 % confidence intervals respectively. Standard errors are clustered at the country level.

could be violated if revenues in treated firms (i.e., firms in more digitalized industries) were rising relative to those in the control group even before the onset of recessions. To test this, we first investigate pre-trends in the raw data by plotting the differences between the mean/median log revenues of high versus low digitalization firms around recession dates (Fig. A2.7). We see that the difference between these groups remains broadly constant in the years leading up to a recession, then narrows shortly after its onset as more digital firms are more resilient..[23]

To check the parallel trends assumption more systematically, we then conduct a placebo test. We create 200 different random recession dummies with a distribution analogous to that of our original recession dummy.[24] We then re-run our baseline specification, replacing our recession dummy with the random dummies. We plot the distribution of the resulting coefficients at each horizon in Fig. A2.8 together with the estimated coefficient in our baseline specification (represented by the vertical red line).

All the coefficients obtained using the random dummies are close to, and centered on, zero—that is, we observe no differential growth in revenues after randomly assigned placebo ‘recessions’. This validates our conclusion that digitalization specifically supports resilience after recessions, distinct from any other time-varying benefits that it may have for firm sales.

5.5. Additional macroeconomic control variables

Our baseline regression includes a constellation of country-sector-time fixed effects and therefore effectively controls for all macroeconomic shocks and their effects across sectors. The inclusion of firm fixed effects further controls for unobservable firm characteristics that do not vary over time. However, our interpretation that digitalization increases resilience during recessions may be spurious if the relationship is really driven by other macroeconomic events/variables that tend to coincide with recessions. We therefore repeat our baseline specification with the addition of controls for the interaction between other macroeconomic variables and digitalization.

First, recessions tend to coincide with periods of financial stress (Dell Ariccia et al., 2008). To check whether financial stress is the true driver of our results, we augment Eq. (2) by interacting the new indicator of financial stress of Ahir et al. (2022) with the Calvino et al. (2018) digitalization dummy.[25] The top left panel of Fig. A2.9 shows the coefficient on the interaction of recessions and digitalization when this extra term is included. Our baseline results (shown in red) are essentially unchanged, in line with our overall interpretation of our findings. If financial stress were instead the true driver of our results, the residual relationship between recessions and digitalization would diverge significantly from the red line.

[23] t-Tests confirm that these differences before the recession are not statistically significant (Fig. A2.7).
[24] Approximately 3 % of the original dummy (for the start of a technical recession) is equal to 1.

[25] The authors use a narrative approach, based on Economist Intelligence Unit (EIU) reports, to construct a quarterly indicator of financial stress for 110 developing and advanced countries over the period 1970–2022.

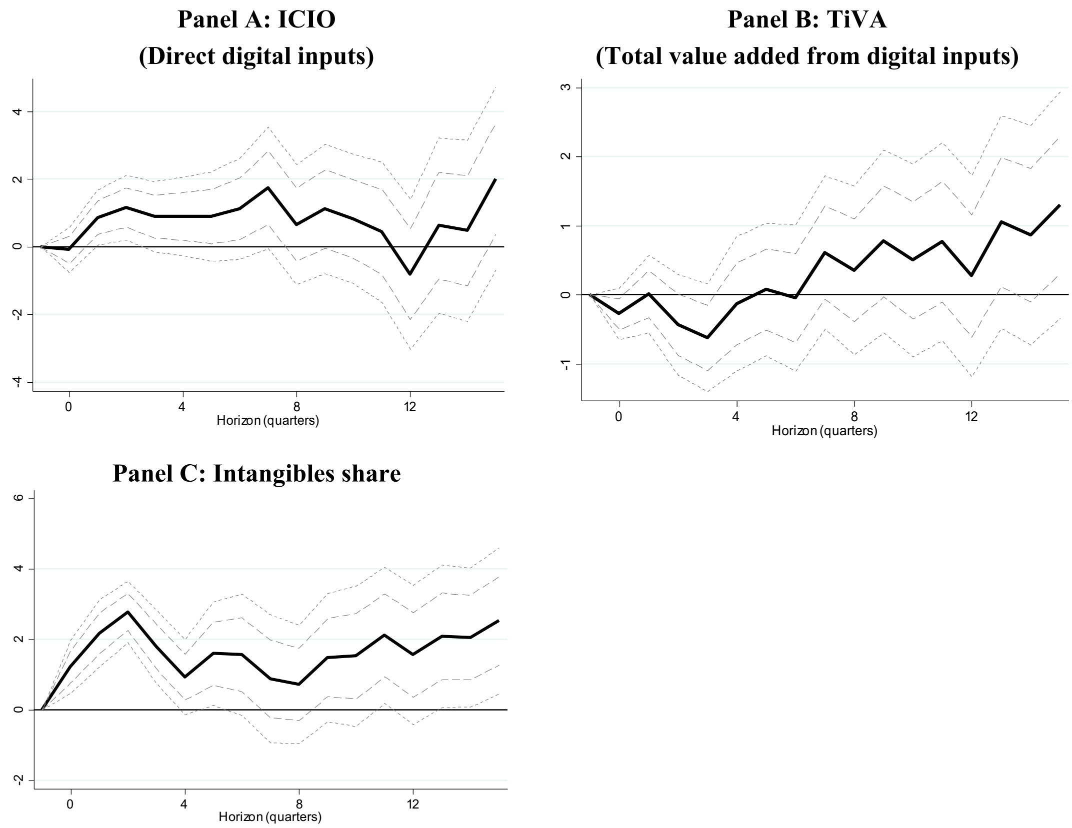


Fig. 9. Robustness: country-industry alternative digitalization measures. differential effect of recession on log revenue for highly digitalized industries vs. average. Notes: Impulse response function based on local projection methods following Jordà (2005) using firm-level quarterly data from countries available (see Table A1.6) 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, $R_{i,t}$ is a dummy which takes value 1 at the start of a technical recession, $D^m \in \left\{D^{ICIO}_{r,i}, D^{TiVA}_{r,i}, D^{Int}_{r,i}\right\}$ is the standardized value of an alternative country-industry-level measure of 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 % and 90 % confidence intervals respectively. Standard errors are clustered by firm and country-time.

A second potential variable that may be driving our results and be correlated with recessions is uncertainty (Ahir et al., 2022; Choi et al., 2018). We again repeat our baseline regression, now controlling for the interaction of country-specific uncertainty—specifically, the World Uncertainty Index of Ahir et al. (2022)—and the digitalization dummy.[26] The estimated impact of digitalization on post-recession revenue (bottom-left panel of Fig. A2.9) is again essentially identical to the baseline results.

Finally, we assess whether inflation is impacting our results. Inflation may affect firms' revenue by increasing price level uncertainty (Choi et al., 2022). However, when repeating the exercise above we again find no significant impact on our main results (top-right panel of Fig. A2.9).

5.6. Correlates of digitalization

Industries that are more digitalized also tend to be less contact intensive, more amenable to teleworking, and hence less exposed to lockdowns. We therefore test whether these features of digitalization are entirely responsible for our results on the benefits of digitalization during the COVID-19 pandemic. In Fig. A2.10, we control in turn for the interaction between recessions and (i) contact intensity, using the sector-wise measure of Jaumotte et al. (2023), (ii) teleworkability, using the measure of Dingel and Neiman (2020), and (iii) overall lockdown exposure, using the measure of Shibata (2020).[27] Our baseline result is largely unaffected, highlighting that digitalization is not simply proxying for these features, but instead supports resilience through a broader range of mechanisms.

5.7. 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:

[26] The index covers an unbalanced panel of 143 individual countries on a quarterly basis from 1952. It reflects the frequency of the word "uncertainty" (and its variants) in the EIU country reports.

[27] Overall lockdown exposure is a composite metric based on the extent to which an industry is teleworkable, essential (i.e., exempted from lockdowns) and social (defined as involving the interaction of individuals to consume goods).

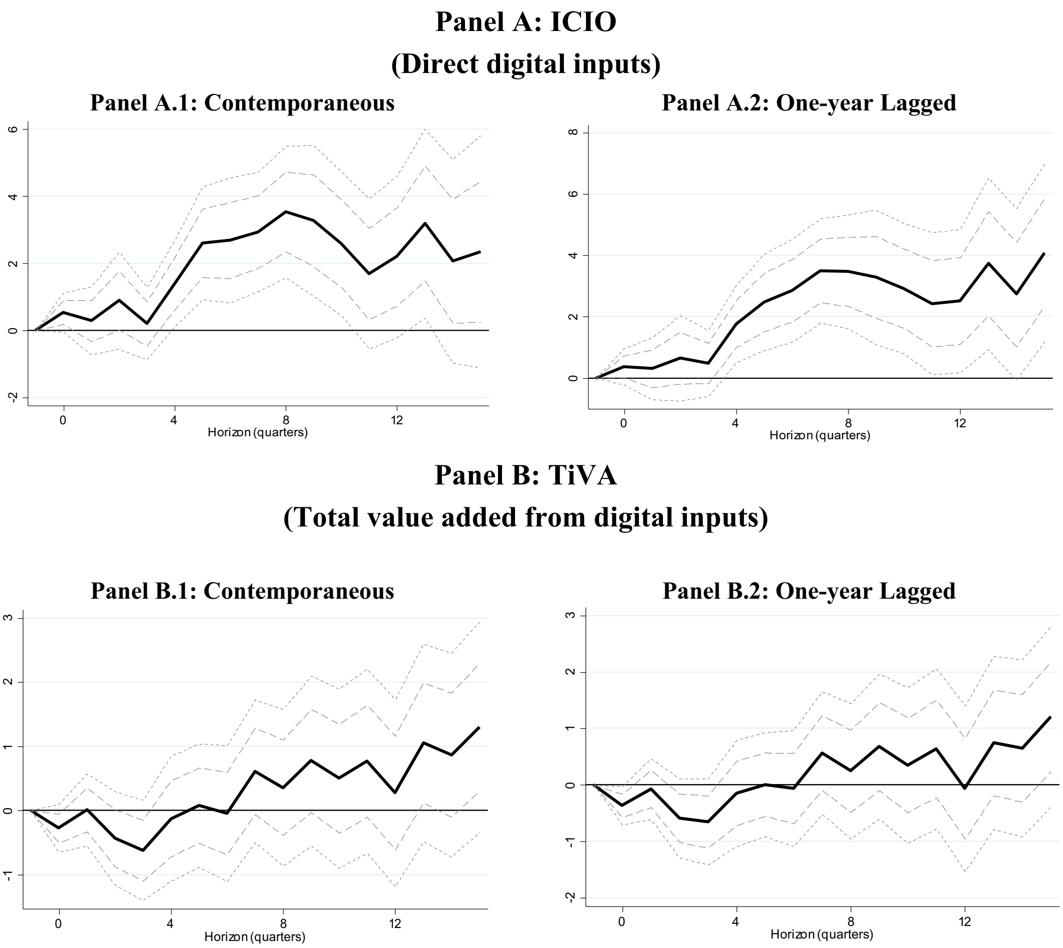


Fig. 10. Robustness: time-varying alternative digitalization measures.
Notes: Impulse response function based on local projection methods following Jordà (2005) using firm-level quarterly data from countries available (see Table A1.6) for the period 2001Q1 to 2021Q1. Estimates based on the regression $\Delta y_{n,i,t+k} = \alpha^k_{ist} + \gamma^k_{nq} + \sum_{j=-k}^{4} \mu^k_j R_{i,t-j} {}^* D^m + \sum_{j=1}^{4} \theta^k_j \Delta y_{n,i,t-j} + \varepsilon^k_{n,i,t}$ 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, $R_{i,t}$ is a dummy which takes value 1 at the start of a technical recession, $D^m \in \left\{ D^{ICIO}_{r,i,t}, D^{TiVA}_{r,i,t}, D^{ICIO}_{r,i,t-1}, D^{TiVA}_{r,i,t-1} \right\}$ is the standardized value of an alternative country-industry-time-varying measure of 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 % and 90 % confidence intervals respectively. Standard errors are clustered by firm and country-time.

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

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^C_r is the standardized Calvino et al. (2018) measure of digitalization in industry r, and α_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:

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

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 Fig. A2.11 of Appendix 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 hiring by more digitalized industries, and roughly 1 percentage point lower growth in transitions out of such industries.

6. 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 higher resilience by reducing medium-term firm revenue losses after a recession. 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

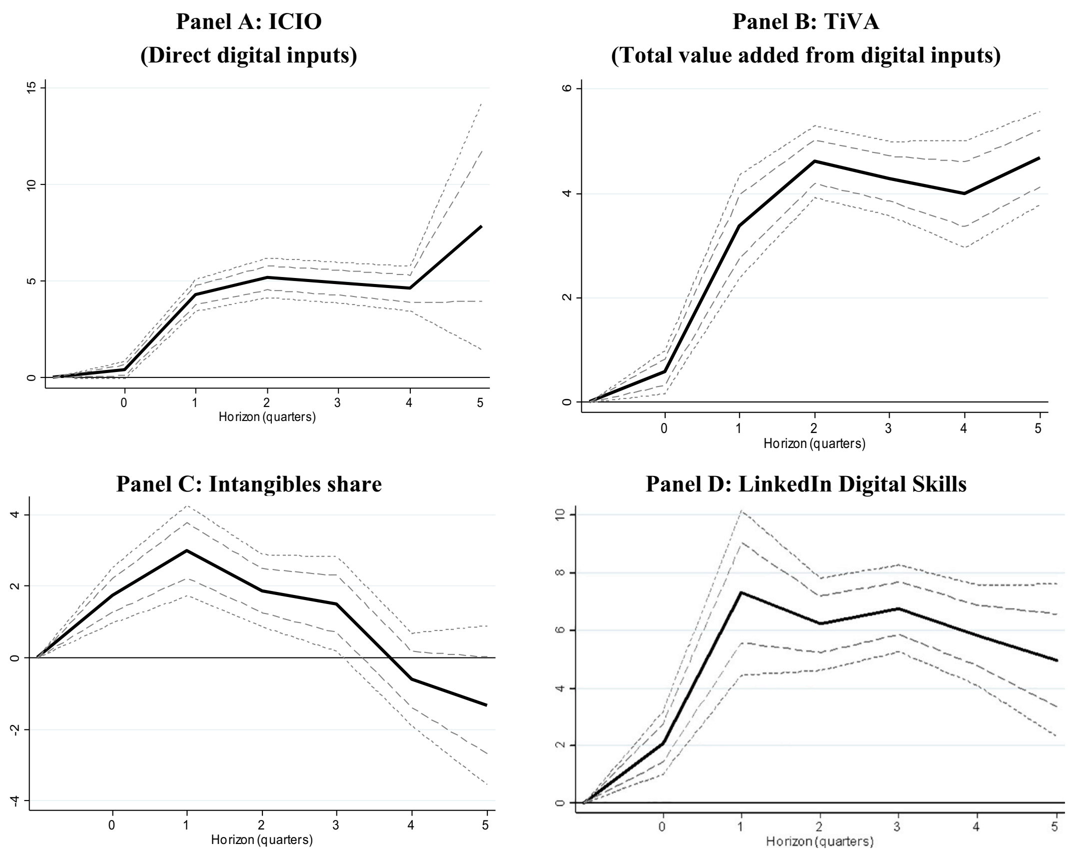


Fig. 11. COVID-19 robustness: country-industry alternative digitalization measures.
Notes: Impulse response function based on local projection methods following Jordà (2005) using firm-level quarterly data from countries available (see Table A1.6) for the period 2016Q1 to 2021Q1. Estimates based on the 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, $R_{i,t}$ is a dummy which takes value 1 at the start of a technical recession from 2019Q4 onwards, $D^m \in \left\{D^{ICIO}_{r,i}, D^{TiVA}_{r,i}, D^{Int}_{r,i}, D^{TechSkills}_{r,i}\right\}$ is the standardized value of an alternative country-industry-level measure of 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 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 % and 90 % confidence intervals respectively. Standard errors are clustered by firm and country-time.

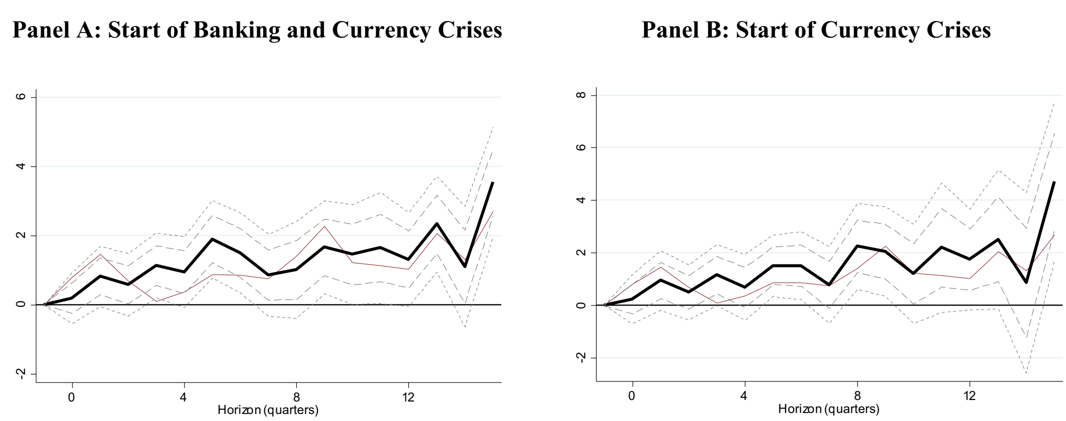


Fig. 12. Robustness: alternative recession measures.
Notes: Impulse response function based on local projection methods following Jordà (2005) using firm-level quarterly data from 75 countries for the period 2001Q1 to 2021Q1. Estimates based on the regression $\Delta y_{n,i,t+k} = \alpha^k_{ist} + \gamma^k_{nq} + \sum_{j=-k}^{4} \mu^k_j R_{i,t-j} {}^* D^m + \sum_{j=1}^{4} \theta^k_j \Delta y_{n,i,t-j} + \varepsilon^k_{n,i,t}$ 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, $R_{i,t}$ is a dummy which takes value 1 at the start of a banking and/or currency crisis, $D^m = D^C_r$ 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 black solid line shows the point estimate for μ^k for different horizons k, while the dashed and dotted lines are the 68 % and 90 % confidence intervals respectively. Standard errors are clustered by firm and country-time. The red line shows the baseline effect using the full sample. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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.

CRediT authorship contribution statement

The authors declare that they have contributed equally to the paper.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

Appendix 1. Annex : Data

Table A1.1
Sample of 75 countries by region.

Africa – AFR (3)	Middle East and Central Asia – MCD (11)	Western Hemisphere –WHD (10)
Botswana	Bahrain	Argentina
Mauritius	Egypt	Brazil
South Africa	Jordan	Canada
	Kazakhstan	Chile
	Kuwait	Colombia
	Oman	Jamaica
	Pakistan	Mexico
	Qatar	Peru
	Saudi Arabia	Trinidad & Tobago
	Tunisia	United States
	United Arab Emirates	

Asia & Pacific – APD (17)	Europe – EUR (34)	
Australia	Austria	Lithuania
Bangladesh	Belgium	Luxembourg
China	Bulgaria	Malta
Hong Kong	Croatia	Netherlands
India	Cyprus	Norway
Indonesia	Czech Republic	Poland
Japan	Estonia	Portugal
Macau	Finland	Romania
Malaysia	France	Russia
New Zealand	Germany	Serbia
Philippines	Greece	Slovakia
Singapore	Hungary	Spain
South Korea	Iceland	Sweden
Sri Lanka	Ireland	Switzerland
Taiwan	Israel	Turkey
Thailand	Italy	Ukraine
Vietnam	Latvia	United Kingdom

Table A1.2
Number of firms and observations by country.

Country	Number of firms	Obs.
United States	4740	388,680
China	4077	334,314
Japan	3085	252,970
India	2672	219,104
Canada	2213	181,466
South Korea	1747	143,254
Taiwan	1693	138,826
Australia	1356	111,192
Hong Kong	1106	90,692
United Kingdom	870	71,340
Malaysia	771	63,222
Thailand	555	45,510
Sweden	525	43,050
Poland	522	42,804

(*continued on next page*)

Table A1.2 (*continued*)

Country	Number of firms	Obs.
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	9758
Finland	117	9594
Saudi Arabia	114	9348
Netherlands	105	8610
New Zealand	105	8610
Mexico	98	8036
Peru	87	7134
Jordan	83	6806
Belgium	75	6150
Ireland	71	5822
Oman	71	5822
Argentina	65	5330
Romania	63	5166
Kuwait	61	5002
Croatia	57	4674
Bulgaria	54	4428
Colombia	49	4018
Austria	45	3690
Cyprus	45	3690
United Arab Emirates	45	3690
Mauritius	44	3608
Luxembourg	39	3198
Jamaica	37	3034
Portugal	36	2952
Tunisia	27	2214
Lithuania	23	1886
Qatar	21	1722
Malta	20	1640
Hungary	18	1476
Bahrain	17	1394
Kazakhstan	15	1230
Estonia	14	1148
Iceland	14	1148
Latvia	14	1148
Trinidad & Tobago	14	1148
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	5433	445,506
Capital Goods	4888	400,816
Technology Hardware and Equipment	2286	187,452
Consumer Durables and Apparel	2032	166,624
Software and Services	2027	166,214
Pharmaceuticals and Biotechnology	1833	150,306

(*continued on next page*)

Table A1.3 (*continued*)

Sector	Number of firms	Obs.
Food, Beverage and Tobacco	1800	147,600
Energy	1714	140,548
Media and Entertainment	1398	114,636
Consumer Services	1315	107,830
Retailing	1291	105,862
Health Care Equipment and Services	1287	105,534
Professional Services	1160	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 75th 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	7230	0.06	0.20	0	1
Banking and currency crises (converted to quarterly)	Reinhart and Rogoff (2009)	63	1960q2-2014q4	7230	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	0.60	0.26	0.25	1
ICIO	OECD Inter-Country Input-Output Tables (OECD, 2021b)	56	2,861,280	0.11	0.20	0	0.86
TiVA	OECD Trade in Value Added database (OECD, 2021c)	58	2,016,718	0.083	0.15	0	0.76
Intangibles	Capital IQ	76	1,301,928	0.11	0.17	0	0.76
Tech Skills	LinkedIn	38	2,254,000	0.099	0.04	0	0.19

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

Most/least digitalized	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
58	Building Products	Textiles, Apparel and Luxury Goods	Road and Rail	Textiles, Apparel and Luxury Goods	Electric Utilities
59	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

Notes: This table shows the most and least digitalized sectors according to each measure. The first row displays the most digitalized of the sixty industries in the Capital IQ data, for each measure, and the last row refers to the least digitalized.

Table A1.8
Descriptive statistics by digitalization level.

Digitalization (Calvino)	Statistic	Firm size (log total assets)	Log revenue to assets	Log profitability	Log return on assets	Firm age	Interest coverage ratio
0.25	mean	4.8	0.2	11.2	−4.4	34.1	8.5
	sd	2.7	0.2	31.0	29.9	29.3	28.2
	min	−2.5	0.0	−178.6	−213.8	1.8	−42.5
	max	10.6	1.0	76.2	27.7	102.8	110.7
0.50	mean	4.8	0.2	8.7	−3.5	31.2	10.6
	sd	2.6	0.2	34.1	29.9	26.8	30.6
	min	−2.5	0.0	−178.6	−213.8	1.8	−42.5
	max	10.6	1.0	76.2	27.7	102.8	110.7
0.75	mean	4.8	0.3	4.4	−2.5	30.5	12.4
	sd	2.3	0.2	30.8	28.1	26.2	34.0
	min	−2.5	0.0	−178.6	−213.8	1.8	−42.5
	max	10.6	1.0	76.2	27.7	102.8	110.7
1.00	mean	4.9	0.2	4.9	−5.7	29.1	10.9
	sd	2.6	0.2	36.6	32.6	26.1	32.5
	min	−2.5	0.0	−178.6	−213.8	1.8	−42.5
	max	10.6	1.0	76.2	27.7	102.8	110.7

Notes: This table shows descriptive statistics within groups defined by digitalization quartiles, where higher values equate to more digitalized industries. The top and bottom 1 % of each variable is winsorized to account for outliers.

Table A1.9
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

Notes: 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).

Table A1.10
Distribution of COVID−19 recessions.

	Country	Recession date		Country	Recession Date
Advanced Economies	Australia	2020q1	Emerging Economies	Kazakhstan	2020q1
	Singapore	2020q1		Philippines	2020q1
	Luxembourg	2020q1		Indonesia	2020q1
	Netherlands	2020q1		Brazil	2020q1
	Norway	2020q1		Hungary	2020q1
	Israel	2020q1		Colombia	2020q1
	Spain	2020q1		Poland	2020q1
	United Kingdom	2020q1		Tunisia	2020q1
	United States	2020q1		Malaysia	2020q1
	Canada	2020q1		Kuwait	2020q1
	France	2020q4		Saudi Arabia	2020q1
	Slovakia	2020q1		Saudi Arabia	2021q1
	New Zealand	2020q1		Russia	2020q1
	Cyprus	2020q1		Venezuela	2021q2
	Iceland	2020q1		Ukraine	2020q4
	Malta	2020q1		Total	15
	Belgium	2020q1			
	Estonia	2020q1			
	Lithuania	2020q1			
	Sweden	2020q1			
	Switzerland	2020q1			
	Austria	2020q4			
	Taiwan	2020q1			
	Czech Republic	2020q1			
	Portugal	2020q1			
	South Korea	2020q1			
	Total	26			

Notes: This table shows the start date of the COVID-19 recessions, defined as described in Sections 2.2 and 4.2.

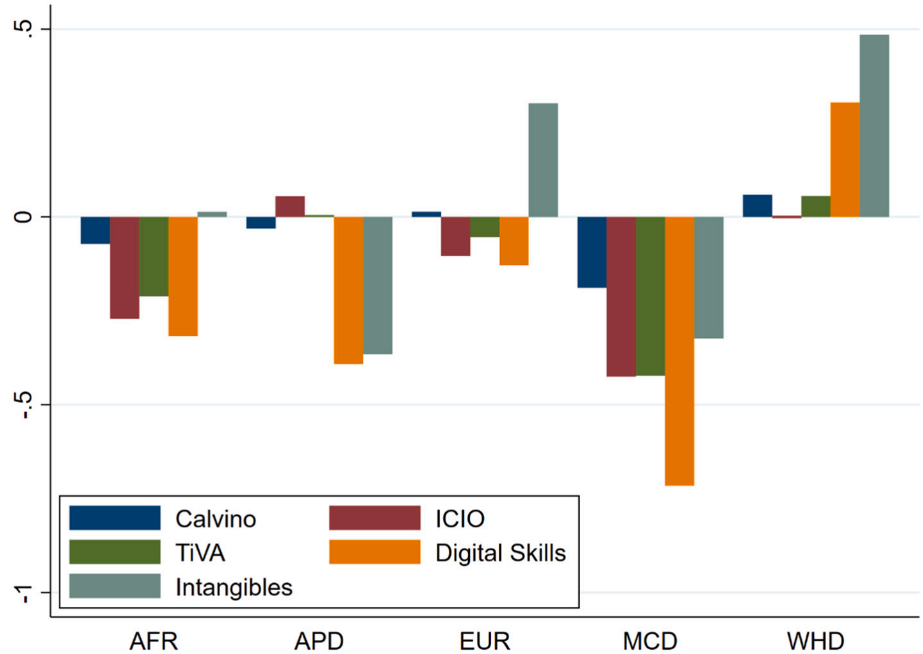


Fig. A1.1. Average digitalization scores by region.
Notes: This graph shows the average standardized score on each of our digitalization measures, across all firms in our sample, by region. AFR = Africa, APD = Asia & Pacific, EUR = Europe, MCD = Middle East and Central Asia, WHD = Western Hemisphere, i.e., North and South America. See Table A1.1 for the specific countries in each grouping in our sample.
(Source: Calvino et al. (2018), OECD (2021b, 2021c), LinkedIn, S&P Capital IQ.)

Fig. A1.2. Average digitalization scores over time.
Notes: This graph shows the average value of each of our time-varying digitalization measures, across all firms in our sample, by year. The ICIO measure shows the average share of direct inputs that come from narrowly defined ICT industries. The TiVA measure shows the average share of total input value added that comes from those same narrowly defined ICT industries, both as direct inputs to production, and as inputs to other inputs to production, and so on.
(Source: OECD (2021b, 2021c).)

Appendix 2. Additional results

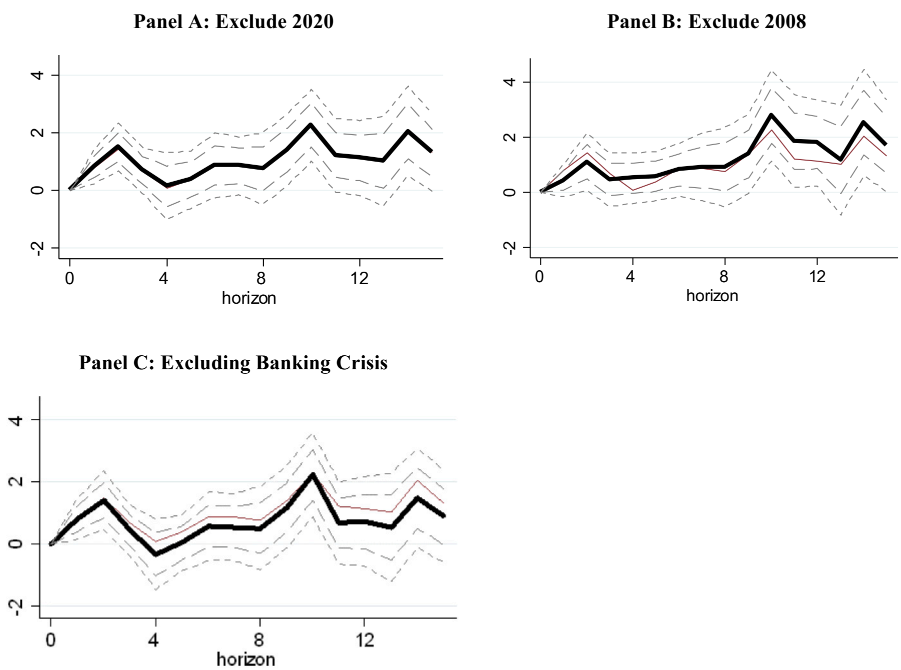


Fig. A2.1. Robustness: excluding GFC, COVID-19 and banking crisis.

Notes: 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, $R_{i,t}$ 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 black solid line shows the point estimate for μ^k for different horizons k, while the dashed and dotted lines are the 68 % and 90 % confidence intervals respectively. Standard errors are clustered by firm and country-time. The red line shows the baseline effect using the full sample.

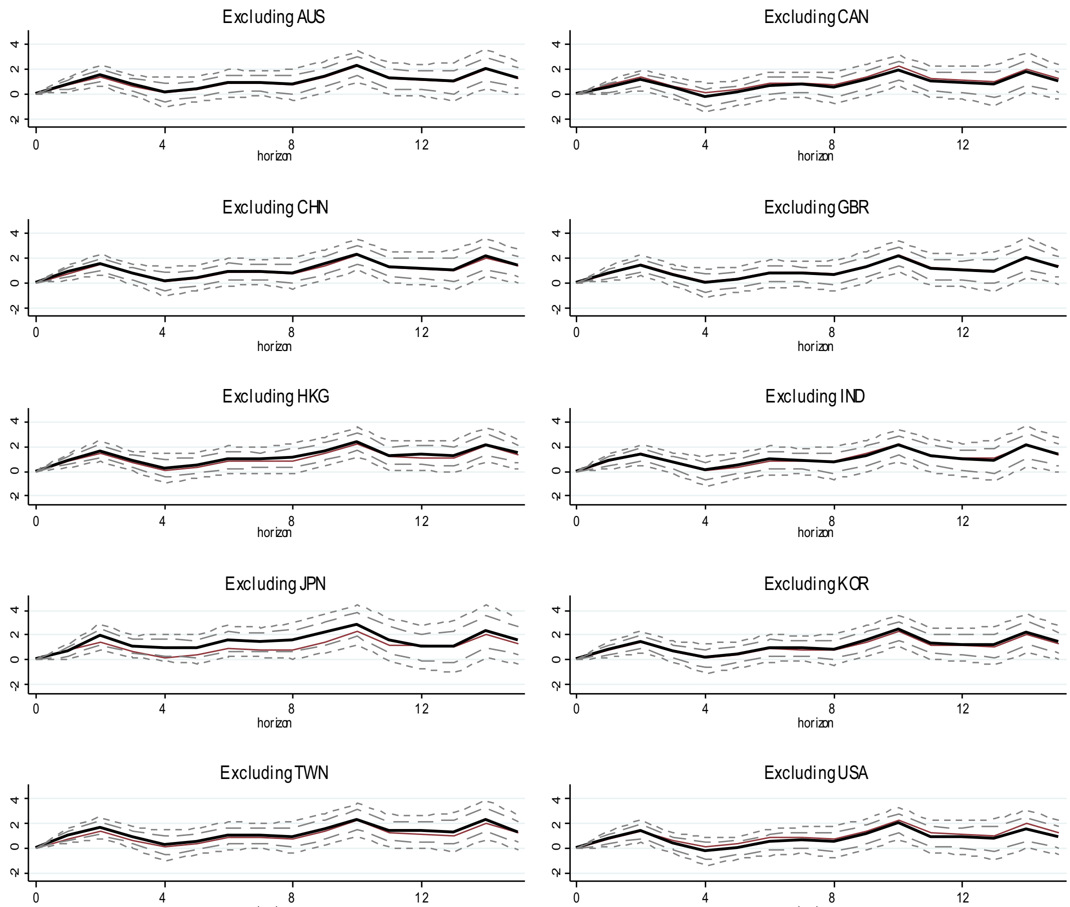


Fig. A2.2. Robustness: excluding countries with most observations.

Notes: 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 $\Delta y_{n,i,t+k} = \alpha^k_{ist} + \gamma^k_{nq} + \sum_{j=-k}^{4} \mu^k_j R_{i,t-j} {}^* D^m + \sum_{j=1}^{4} \theta^k_j \Delta y_{n,i,t-j} + \varepsilon^k_{n,i,t}$ 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 black solid line shows the point estimate for μ^k for different horizons k, while the dashed and dotted lines are the 68 % and 90 % confidence intervals respectively. Standard errors are clustered by firm and country-time. The red line shows the baseline effect using the full sample.

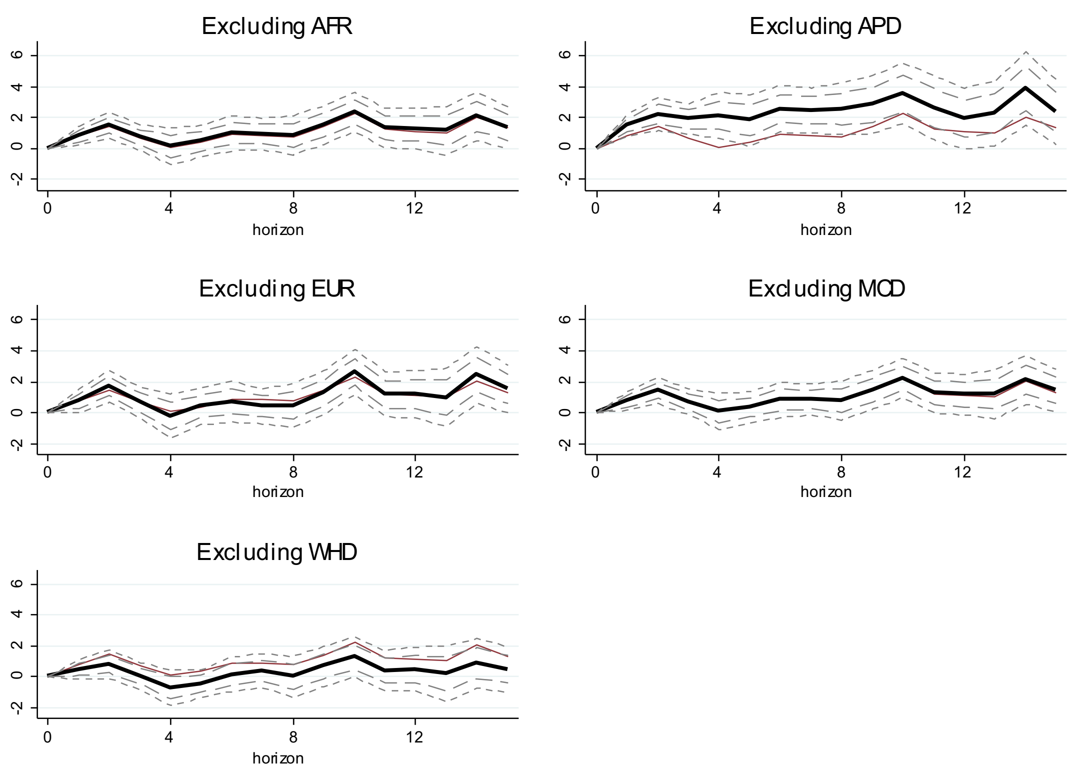


Fig. A2.3. Robustness: excluding one region at a time.

Notes: 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, $R_{i,t}$ 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 black solid line shows the point estimate for μ^k for different horizons k, while the dashed and dotted lines are the 68 % and 90 % confidence intervals respectively. Standard errors are clustered by firm and country-time. The red line shows the baseline effect using the full sample.

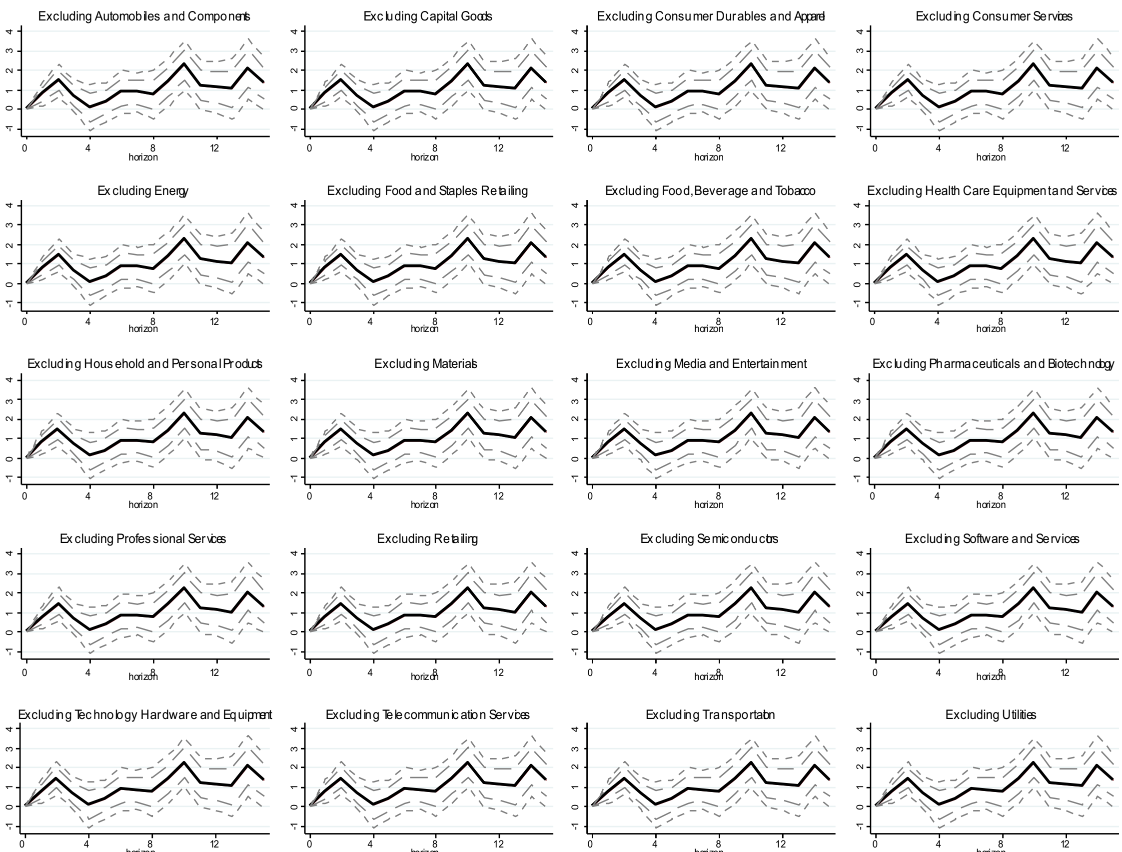


Fig. A2.4. Robustness: excluding one sector at a time.
Notes: Responses are calculated excluding one 2-digit sector at a time. Impulse response function based on local projection methods following Jordà (2005) using firm-level quarterly data from 75 countries for the period 2001Q1 to 2021Q1. Estimates based on the regression $\Delta y_{n,i,t+k} = \alpha^k_{ist} + \gamma^k_{nq} + \sum_{j=-k}^{4}\mu^k_j R_{i,t-j} {}^* D^m + \sum_{j=1}^{4}\theta^k_j \Delta y_{n,i,t-j} + \varepsilon^k_{n,i,t}$ 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, $R_{i,t}$ 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 % and 90 % confidence intervals respectively. Standard errors are clustered by firm and country-time. The red line shows the baseline effect using the full sample.

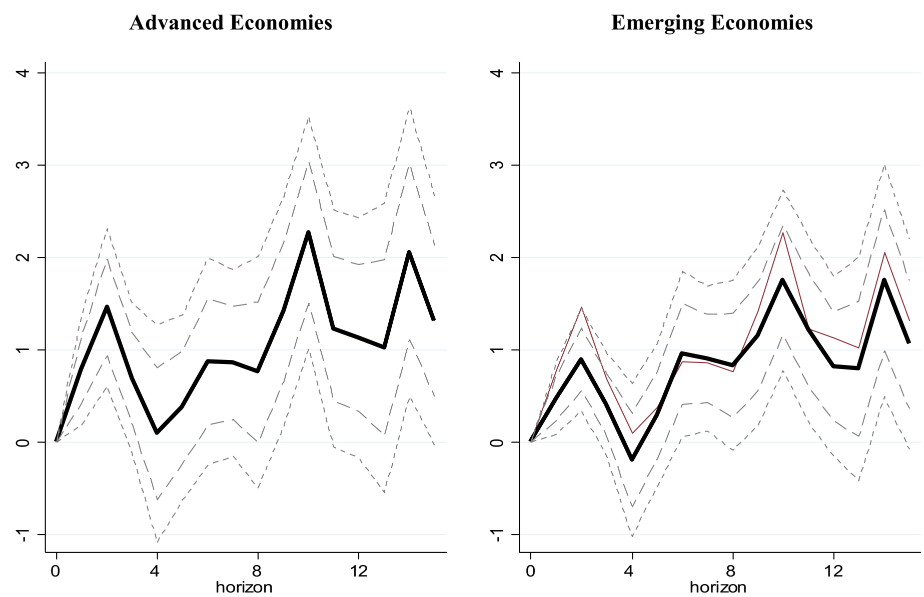


Fig. A2.5. Robustness: country income level.

Notes: 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, $R_{i,t}$ 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 black solid line shows the point estimate for μ^k for different horizons k, while the dashed and dotted lines are the 68 % and 90 % confidence intervals respectively. Standard errors are clustered by firm and country-time. The red line shows the baseline effect using the full sample.

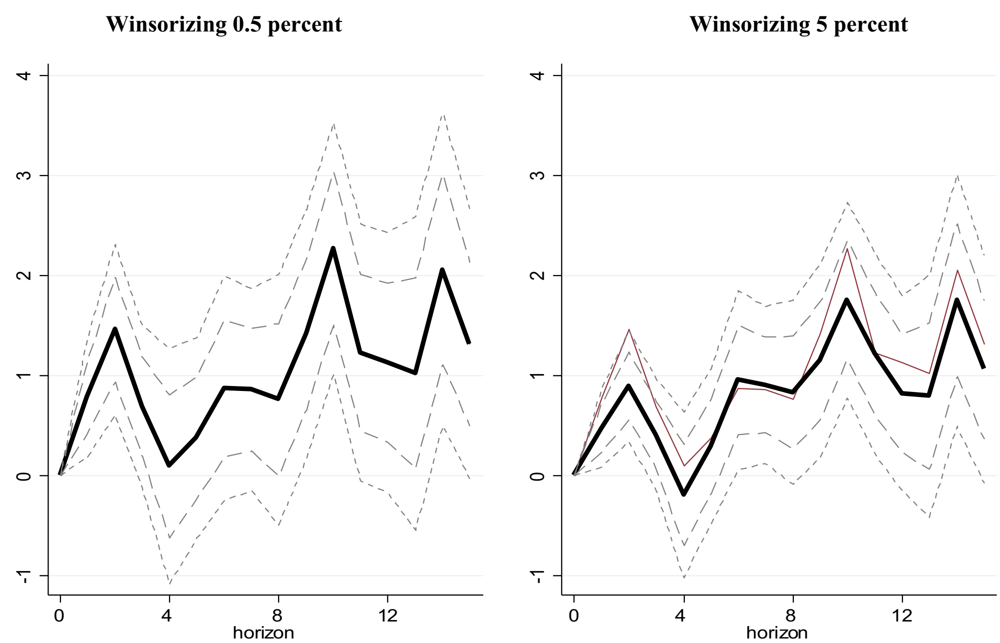
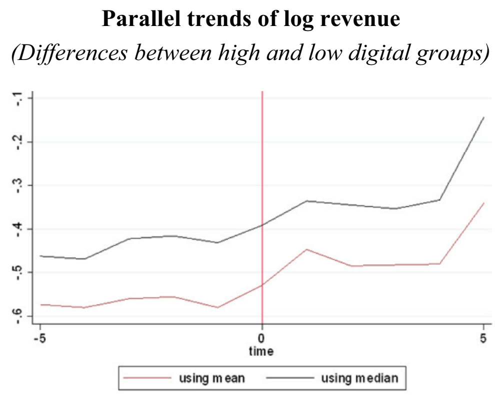


Fig. A2.6. Robustness: different winsorization thresholds.

Notes: 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, $R_{i,t}$ 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 black solid line shows the point estimate for μ^k for different horizons k, while the dashed and dotted lines are the 68 % and 90 % confidence intervals respectively. Standard errors are clustered by firm and country-time. The red line shows the baseline effect using the full sample.



T-test results

	Pr(T > t)	
Quarter	**Using Mean**	**Using Median**
Recession	0.228	0.337
-1	0.241	0.367
-2	0.198	0.365
-3	0.227	0.348
-4	0.204	0.321
-5	0.274	0.354

Fig. A2.7. Robustness: parallel trends.
Notes: The figure plots the difference in the mean/median value of log revenue around recessions (vertical red line) for high vs. low digitalization groups over the full sample. The table reports the *p*-values from *t*-tests of the null hypothesis that the differences are equal to zero.

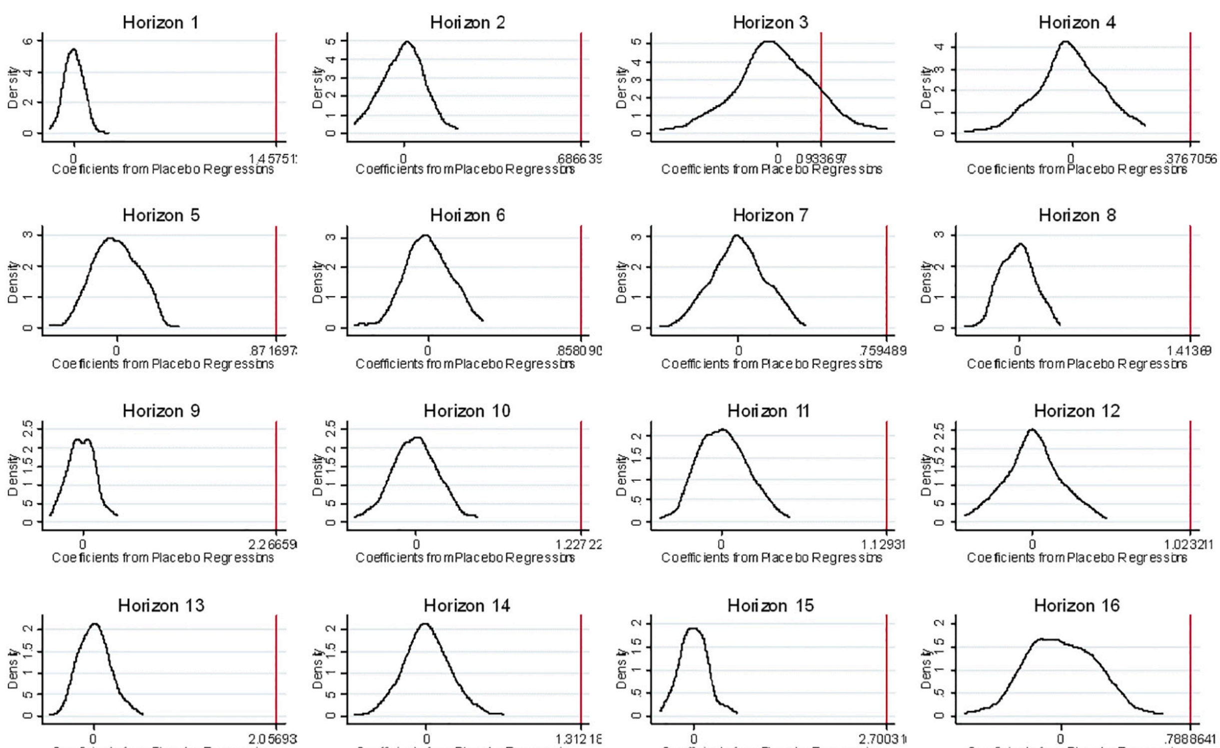


Fig. A2.8. Robustness: placebo test.
Notes: The figure plots the distribution of the coefficients obtained at each horizon when re-running our baseline regression using each of 200 different placebo dummies. Results are based on local projection methods following Jordà (2005) using firm-level quarterly 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, $R_{i,t}$ is our random recession dummy. $D^m = D^C_r$ 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.

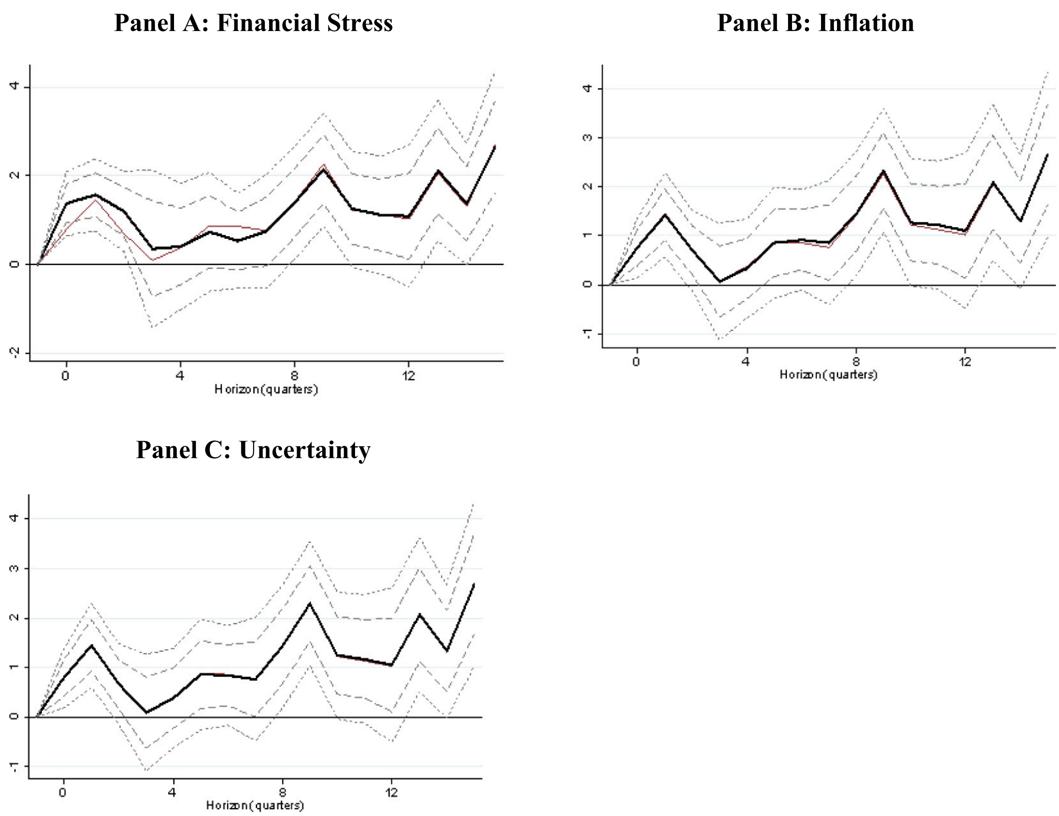


Fig. A2.9. Robustness: controlling for other macroeconomic factors.

Notes: 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 $\Delta y_{n,i,t+k} = \alpha^k_{ist} + \gamma^k_{nq} + \sum_{j=-k}^{4} \mu^k_j R_{i,t-j} {}^* D^m + \sum_{j=-k}^{4} \nu^k_j M_{i,t-j} {}^* D^m + \sum_{j=1}^{4} \theta^k_j \Delta y_{n,i,t-j} + \varepsilon^k_{n,i,t}$ 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, $R_{i,t}$ 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. Interaction of various macro variables $M_{i,t-j}$ with the digitalization dummy are included as controls. The regression is estimated separately for different horizons k over a four-year period. The black solid line shows the point estimate for μ^k for different horizons k, while the dashed and dotted lines are the 68 % and 90 % confidence intervals respectively. Standard errors are clustered by firm and country-time. The red line shows the baseline effect using the full sample.

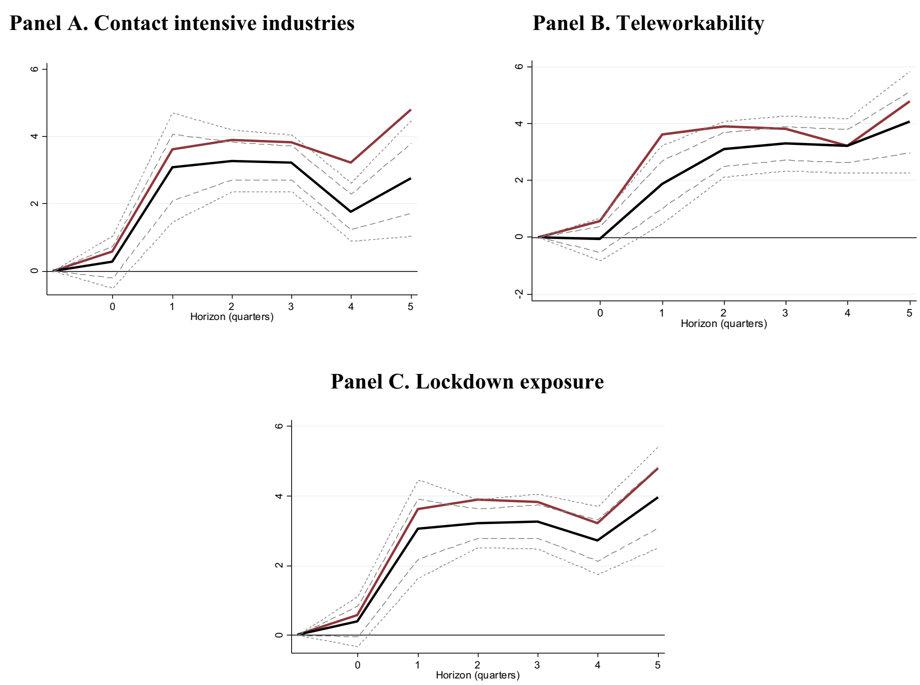


Fig. A2.10. Robustness: controlling for correlates of digitalization.

Notes: 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 $\Delta y_{n,i,t+k} = \alpha^k_{ist} + \gamma^k_{nq} + \sum_{j=-k}^{4} \mu^k_j R_{i,t-j} {}^* D^m + \sum_{j=-k}^{4} \zeta^k_j R_{i,t-j} {}^* M_r + \sum_{j=1}^{4} \theta^k_j \Delta y_{n,i,t-j} + \varepsilon^k_{n,i,t}$ 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, $R_{i,t}$ is a dummy which takes value 1 at the start of a technical recession from 2019Q4 onwards, $D^m = D^C_r$ is the standardized value of the Calvino et al. (2018) measure of industry-wise digitalization, M_r is an industry-wise measure of contact intensity or teleworkability or lockdown exposure, 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 five-quarter period. The black solid line shows the point estimate for μ^k for different horizons k, while the dashed and dotted lines are the 68 % and 90 % confidence intervals respectively. Standard errors are clustered by firm and country-time. The red line shows the baseline effect using the full sample.

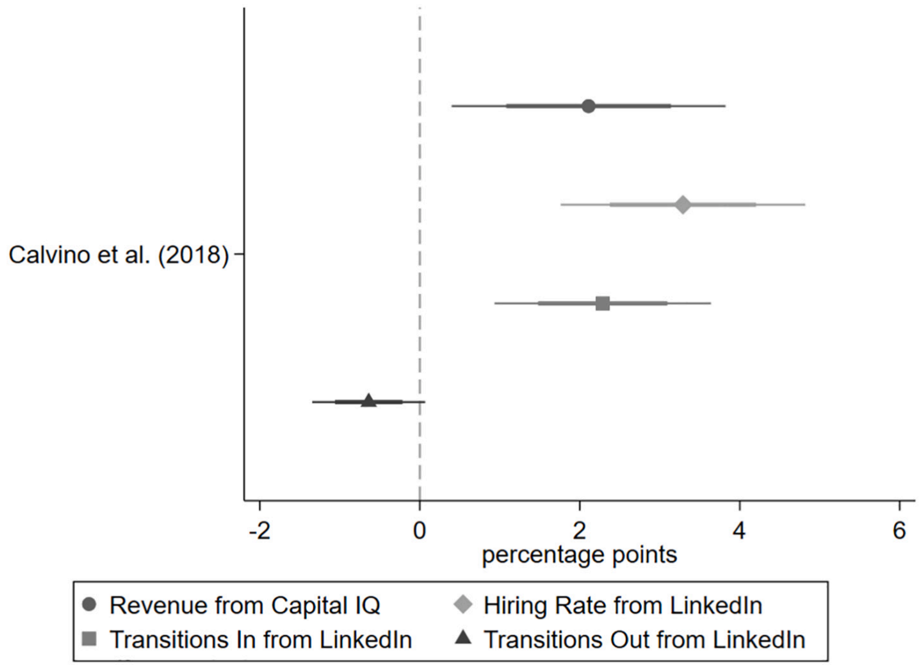


Fig. A2.11. Robustness: estimations using alternative specification.
Notes: This figure shows the results from estimating the impacts of digitalization using the alternative methodology of Duval et al. (2020). The top coefficient plotted is estimated from Capital IQ firm data in a regression of the form $\Delta y_{n,i} = \alpha_i + \alpha_s + \mu{*}D_r^C + \epsilon_{n,i}$, 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 % and 90 % confidence intervals respectively. Standard errors are clustered by country.

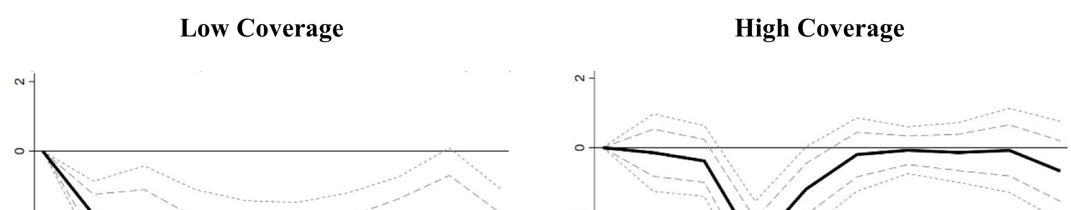


Fig. A2.12. Effect of COVID-19 recessions on outward transitions for highly digitalized industries vs. average, by job retention scheme coverage.
Notes: Impulse response function based on local projection methods following Jordà (2005) using industry-level quarterly data from 40 countries for the period 2016Q1 to 2022Q1. Estimates based on the regression $\Delta y_{r,i,t+k} = \alpha_{it}^k + \alpha_{ri}^k + \sum_{j=-k}^{4}\mu_j^{k,lo} R_{i,t-j}{*}D_r^C{*}(D\_JRS_i = 0) + \sum_{j=-k}^{4}\mu_j^{k,hi} R_{i,t-j}{*}D_r^C{*}(D\_JRS_i = 1) + \sum_{j=1}^{4}\theta_j^k \Delta y_{r,i,t-k} + \epsilon_{r,i,t}$ 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, $R_{i,t}$ 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. D_JRS_i is a dummy that takes value zero/one if the variable JRS_i is below/above the median in country i, JRS_i is the share of workers covered by a job retention scheme in May 2020, taken from the OECD Employment Outlook 2022 following Jaumotte et al. (2023). 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 % and 90 % confidence intervals respectively. Standard errors are clustered at the country level.

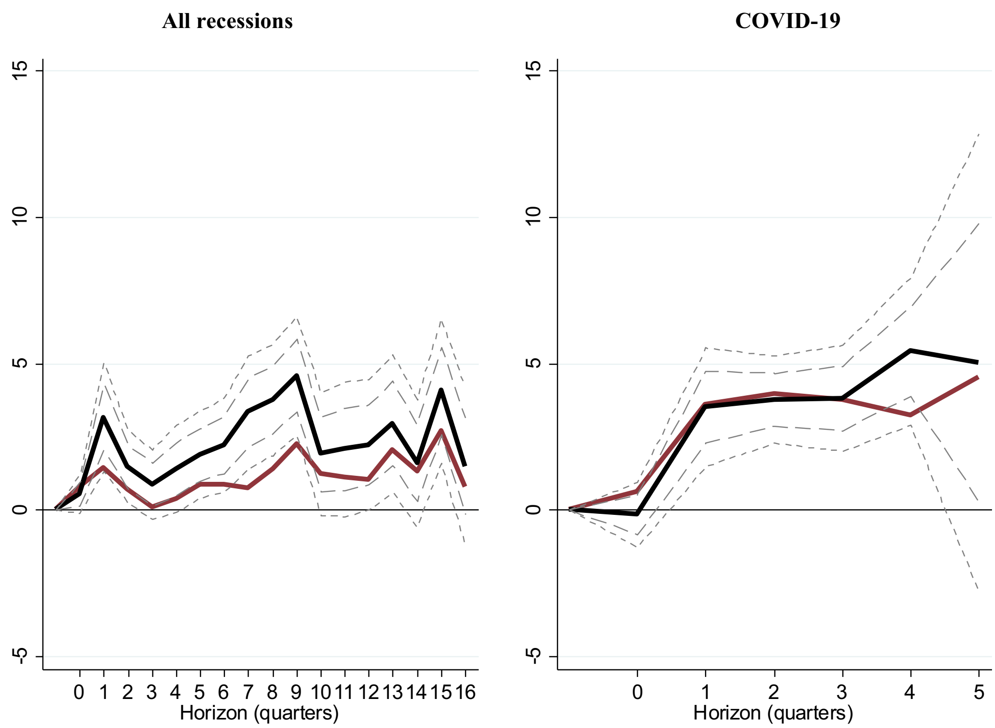


Fig. A2.13. Robustness: including emerging markets only.
Notes: Impulse response function based on local projection methods following Jordà (2005) using firm-level quarterly data from 75 countries for the periods 2001Q1 to 2021Q1 and 2016Q1 to 2021Q1 respectively. The left-hand chart repeats Fig. 4 with the sample restricted to emerging markets alone; likewise the right-hand chart for Fig. 7. In each case, the red line shows the baseline effect using the full sample.

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