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Advanced digital technologies and industrial resilience during the COVID-19 pandemic: A firm-level perspective

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Advanced digital technologies and industrial resilience during the COVID-19 pandemic: A firm-level perspective*

Elisa Calza‡ Alejandro Lavopa§, Ligia Zagato**

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Abstract

The advanced digital production (ADP) technologies of the fourth industrial revolution (4IR) are expected to reshape the way industrial production takes place. These technologies offer new windows of opportunities for developing countries to catch up with the world technological frontier, but, at the same time, they pose new challenges and risks. This paper uses a novel firm-level data set collected by UNIDO and partners around the world to investigate the extent to which these technologies are diffused in developing countries, the main factors supporting their adoption and the role played by these technologies during the COVID-19 pandemic. Three key findings emerge from the analysis: (1) the diffusion of these technologies is still very limited to a handful of firms; (2) large firms, firms operating within global value chains and firms with existing innovative capabilities are more likely to adopt ADP technologies; and (3) advanced digitalization has contributed to the robustness of firms as they address the COVID-19 crisis and supported their readiness to act and respond quickly and adapt to the new context. The findings of the paper are expected to inform policymakers in the design of industrial recovery policies that can strengthen future industrial resilience in developing and emerging economies.

Keywords: Industrial development, digital technologies, resilience; fourth industrial revolution, firm-level analysis, COVID-19.

JEL Codes: O12, O14, O33

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1 Introduction

A new wave of emerging digital technologies, often clustered together under the labels "fourth industrial revolution" (4IR) or "Industry 4.0", is creating a new paradigm of industrial production. Internet of things (IoT), artificial intelligence (AI) and robotics, among other technologies, are revolutionizing the industrial process and inducing important changes along value chains and within firms.

As the rhythm of technical progress is rapid, many questions are still unanswered: What is the—expected and real—impact of these new digital production technologies at the firm level, especially on productivity, employment and skills requirements? Which factors can foster or inhibit the diffusion of these technologies? To what extent are these production technologies being adopted among developing countries' manufacturing firms? Most of these issues remain open and still unexplored. As the COVID-19 pandemic seems to have accelerated the pace of digitalization, addressing these questions is becoming increasingly urgent.

Answering these questions requires new empirical, firm-level evidence on the adoption and impact of the new technologies. Despite being considered potential game-changers for industrial competitiveness, the available evidence on the adoption and use of these technologies by manufacturing firms in developing and emerging countries is still very limited.

The need for more research on this matter has become even more evident with the spread of the COVID-19 pandemic. The adoption of digital technologies is regarded as playing a key role in shaping the resilience of firms against the negative impact of the pandemic crisis. By the same token, these technologies are also expected to be major tools in the recovery from the crisis. The empirical basis for these arguments remains limited, however, in the context of developing countries, mainly due to the lack of internationally comparable micro-data on the diffusion of digital technologies and the impact that the pandemic crisis has had on manufacturing firms across the developing world.

To fill these gaps, the United Nations Industrial Development Organization (UNIDO) promoted an original data collection exercise to assess the impact of COVID-19 on manufacturing firms in 26 developing and emerging economies in Africa, Asia and Latin America: the *UNIDO survey on the impact of the COVID-19 pandemic on manufacturing firms*.[5] The information collected offers original insights on the consequences that the COVID-19 crisis had across different countries, industries and firms. The survey also includes a module inquiring about the industrial application of a wide range of digital

[5] For more information see https://www.unido.org/covid19_surveys.

technologies in production processes and in customer relations, following the approach put forward in UNIDO's *Industrial Development Report 2020* (UNIDO 2019).

Drawing on this original data set from the survey, this paper aims to provide new insights on the analysis of industrial digitalization in developing and emerging economies. Taking advantage of the information on the impact of the COVID-19 pandemic on surveyed manufacturing firms, this paper also tries to shed some light on the interplay between advanced digital technologies and the resilience of firms against extreme events like the pandemic.

The contribution of the paper is thus threefold. First, it offers a unique picture of the diffusion of advanced digital production (ADP) technologies among manufacturing firms around the developing world. The strong heterogeneities that exist both across and within world regions are highlighted, setting the stage for a more informed discussion on the challenges that the digital divide can bring to competitive leapfrogging, catch-up and structural change.

Second, the paper moves beyond this descriptive approach and examines the determinants of advanced digital technology adoption in the context of developing countries. To do so, it empirically explores whether the size of the firm, the industry of operations and the type of integration in international production networks, among other factors, affect the absorption of the latest iteration of digital production technologies. This analysis helps identify firm-level features that should be considered when formulating industrial policies to foster the diffusion of advanced digital production technologies.

Third, the paper takes full advantage of the collected COVID-19-related information and analyses the relationship between digitalization and industrial resilience during the pandemic crisis. It does so from two perspectives, mirroring the distinction between robustness and readiness as main dimensions of resilience (Andreoni 2021). In terms of robustness, it investigates the factors that have contributed to shaping the economic impact of the pandemic crisis on manufacturing firms, exploring whether digitally advanced firms have been better suited to weather the crisis. In terms of readiness, it turns to the response strategies undertaken by manufacturing firms to react to the crisis and adapt to the "new normal", looking for eventual differences between digitally advanced firms and the rest. The results contribute to the identification of key factors that can support future resilience in manufacturing firms in developing countries.

2 The fourth industrial revolution in the empirical literature

Industrial value creation has gone through radical changes during the last 250 years. These changes have not followed a linear course, but have occurred in the midst of so-called industrial revolutions, which can be characterized by the transition from human to machine work with increases in productivity (Tim Stock et al. 2018). The invention of the steam engine, the mechanization of simple tasks and the construction of railroads triggered the first industrial revolution (1RI) between 1760 and 1840. Later, the advent of electricity, the assembly line and mass production gave rise to the second industrial revolution (2IR) between the late 19th and early 20th centuries. With the third industrial revolution (3IR), in the 1960s, new forms of microelectronic and robotic technologies were introduced into companies' production systems. This was accompanied by a first wave of increasing the level of automation in manufacturing and assembly through Computer Integrated Manufacturing (CIM) (Tim Stock et al. 2018).

In recent years, the global industrial landscape has drastically changed due to successive technological advancements, developments and innovations (Lampropoulos, Siakas, and Anastasiadis 2019). The increase of automation, robotics and digital technologies in applications, coupled with new developments in both nano- and bio-technologies, has been altering manufacturing production and processes technologies, in what has been called the fourth industrial revolution (4IR) (Andreoni, Chang, and Labrunie 2021).

Closely related to the 4IR, the concept of Industry 4.0 has been attracting increasing interest from both practitioners and academics (Fatorachian and Kazemi 2018; Liao et al. 2017; Papadopoulos et al. 2021; Pereira and Romero 2017). Industry 4.0 can be regarded as a highly integrated, digitalized, automated and autonomous, and efficient manufacturing environment (Lampropoulos, Siakas, and Anastasiadis 2019).

While there is still open debate on the magnitude of the impact of digital technologies and the 4IR on industrial organization, and on whether the current changes can be regarded as an industrial revolution, there is no doubt that the changes in the patterns of value creation and distribution brought about by the industrial application of advanced digital technologies are marking an epochal change in industrial development, opening up new and previously unavailable opportunities (Lee et al. 2020; OECD 2017; Stock and Seliger 2016).

Industry 4.0 stands for a new way of organization and control of complete value-added systems to fulfil individual customer needs at the cost of mass production. The idea of an Industry 4.0 has “smart manufacturing”–or “smart factory”–as its central element (Frank, Dalenogare, and Ayala 2019; Kagermann, Wahlster, and Helbig 2013). It considers the integration of the factory with the entire product lifecycle as well as supply chain activities (Wang et al. 2016; Dalenogare et al. 2018), thanks to advanced digital technologies that, by enhancing connectivity, flexibility and production functionality, enable greater coordination efficiencies, condition monitoring and process optimization, both within firms and along supply chains. In this way, ADP technologies bridge the physical and digital worlds, leading to the development of cyber-physical systems relying on IoT to integrate workers, products, resources and production systems, affecting even the way people work (Monostori et al. 2016; Stock et al. 2018). Based on Industry 4.0 principles and resources, productivity and efficiency can be continuously improved, enabling companies to develop new ways of creating value and novel business models (Kagermann, Wahlster, and Helbig 2013; Monostori et al. 2016).

This new model of production relies on the application of ADP technologies to industrial processes. Representing the latest evolution of production technologies, ADP technologies include, among others, the industrial Internet of Things (IoT), big data analytics, artificial intelligence (AI), additive manufacturing, advanced robotics, and cobots (see Table 1).

Table 1: Advanced digital production (ADP) technologies: Definitions and descriptions

Technology	Brief definition
Additive manufacturing (3D printing)	Commonly known as 3D printing, it refers to the use of special printers to create three-dimensional physical objects from 3D model data by adding layer-upon-layer through material extrusion, directed energy deposition, material jetting, binder jetting, sheet lamination, vat polymerization and powder bed fusion. AM is opposed to subtractive manufacturing methodologies, which use molds or rotating milling cutter to remove material from a solid block of material.
Advanced robotics and cobots	Robots are machines programmed by a computer capable of carrying out a series of more or less complex actions automatically. An industrial robot is an automatically controlled, reprogrammable and multipurpose manipulator in three or more axes (either fixed in a place or mobile), which can be used in industrial automation applications such as manufacturing processes (welding, painting and cutting) or handling processes (depositing, assembling, sorting and packing). Cobots are robots intended to physically interact with humans. Designed to learn and adapt to new tasks, they are built with passive compliance features and integrated sensors to adapt to external forces. They tend to be cost-effective, safe and easy-to-use, and are suitable for small-scale production and reduced production cycles. They are also portable and easy to configure/reconfigure to perform different tasks.
Artificial intelligence (AI)	Branch of computer science seeking to develop devices that simulate the human capacity to reason and make decisions. The term usually refers to the employment of AI techniques (such as machine learning, deep learning, computer vision, natural language processing, neural networks, fuzzy logic and self-organizing maps) to provide machines and systems with human-like cognitive capabilities, such as learning, adapting, solving problems and perception.
Big data analytics	Data characterized by greater volume (vast amount of data), velocity (frequency or speed by which data is generated, becomes available and changes over time), variety (different sources and format of complex data, either unstructured or structured) and granularity than ever available previously.
Cloud computing	Ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (such as networks, servers, storage, applications and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction.
Industrial Internet of Things (IoT)	Next iteration of the internet, where information and data are no longer predominantly generated and processed by humans—which has been the case for most of the data created so far—but by a network of interconnected smart objects, embedded in sensors and miniature computers, able to sense their environment, process data and engage in machine-to-machine communication .
Machine learning	An application of AI, machine-learning systems use general algorithms to figure out on their own how to map inputs to outputs, typically being fed by extensive sample datasets. These systems can improve their performance on a given task over time by amassing experiences and large volumes of data such as big data.

Source: Authors' elaboration based on UNIDO (2019)

2.1 An emerging empirical literature

The debate around ADP technologies and Industry 4.0 has grown substantially over the last decade—and the potentially disruptive impact of these new technologies on employment in mature industrial economies took central stage in the academic and policy debates from the very start.

Two opposing views have dominated the debate so far. A more optimistic perspective perceives these technologies as a new source of opportunities, including in terms of productivity and job creation. Conversely, the more skeptical view argues that "this time is different" and the eventual benefits derived from the diffusion of Industry 4.0 will not compensate for the risk of automation, as these technologies will not generate as many (good) jobs as workers, especially low-skill workers, who will be displaced. In this regard, examining the impact of the increase in industrial robot usage on US labour markets between 1990 and 2007, Acemoglu and Restrepo (2018) find that industrial robot adoption was negatively correlated with employment and wages during this time period. Frey and Osborne (2017) find that almost half of total US employment is at risk of being automated over the next two decades.

More optimistic arguments have emphasized the capacity of these technologies to boost economic growth and generate more and better jobs (Atkinson and Wu 2017; Frey and Osborne 2017; Graetz and Michaels 2018; Pérez 2010). Alexopoulos and Cohen (2016) stress that positive technology shocks have, historically, increased job opportunities and employment overall. Mandel (2017) finds that job losses at department stores were more than made up for by new opportunities in e-commerce. The *European Commission Report on Robotics and Employment* (2016) examined the use of industrial robots in Europe, finding no evidence that the use of industrial robots has had any direct effect on employment, though firms utilizing robotics do have significantly higher levels of labour productivity. Bessen (2018) argues that robotics and automation can have a positive effect on employment if they improve productivity in markets where there is a large amount of unmet demand. The majority of the studies mentioned focused on the implications associated with the spread of AI and robotization, but some other works have also considered other types of advanced digital technologies, such as 3D printing (Berman 2012) and IoT (Lampropoulos, Siakas, and Anastasiadis 2019).

While these works mostly approach the analysis of these new technologies from a more aggregate perspective, the firm-level literature on the adoption and implications of ADP technologies remains rather scant (Seamans and Raj 2018). The few existing works explore the drivers of adoption (for instance, Brynjolfsson and McElheran 2016; Cirera et al 2021) and test their impact (Cusolito, Lederman, and Pena 2020; Gal et al. 2019; Seamans and Raj 2018). Brynjolfsson et al. (2011) use a US firm census and find that firms implementing big data and data-driven decision-making have 5-6 percent higher output and productivity. For firms in OECD countries, improving data quality and access is associated with a 14 percent increase in labour productivity (OECD 2017). Using the data from the European Manufacturing Survey (EMS), a European Commission study shows that companies using robots achieve significantly higher levels of productivity but have no direct effect on firm-level employment (European Commission 2016). Besides productivity, other performance indicators have also been used, such as output, value added, or sales or employment growth. Brynjolfsson and McElheran (2016) find evidence of a causal relationship between firm performance and data-driven decision-making: the value added for firms implementing data analysis in their decisions is 3 percent greater than for non-implementing ones.

The scarcity of micro-level empirical analyses on ADP technologies is mostly due to two interlinked reasons. First, the novelty of the phenomenon and its limited diffusion–in general, and in a developing context in particular—make it more challenging to soundly assess their firm-level impacts even in advanced economies. Although this has become a priority for the agenda of various countries, the adoption of ADP technologies seems to be still at an initial stage: even in advanced economies, firms are only slowly engaging with these technologies (Andreoni and Anzolin 2019). Using data from the *2018 Annual Business Survey*, Zolas et al (2020) found that in the United States, even though digitalization is quite widespread, the adoption of advanced technologies is still rare and generally skewed towards larger and older firms.

Second, even when data is available, it might not be adequate for an in-depth analysis of the industrial application of ADP technologies (Seamans and Raj 2018). In fact, while several data sources offer rather comprehensive figures about global trends in the diffusion of a specific new technology (such as the information on the number of robots by the IFR), equivalent firm-level information is rarely available. This makes it challenging to explore the relationship of these technologies to firm characteristics or firm performance indicators.

Some firm-level information on the application of ADP technologies can be found in the executive surveys carried out by international consulting firms, mostly in industrialized countries (PwC 2018; Renjen 2020; McKinsey & Company 2020). However, since these surveys tend to consider selected large companies and multinational companies (MNCs) operating in different manufacturing and service sectors, the collected data is usually not broadly representative nor adequate to conduct empirical analyses.

Firm-level surveys such as the European Manufacturing Survey (EMS), the Eurostat ICT Usage and E-commerce in Enterprises survey, and the Investment Survey conducted by the European Investment Bank (EIBIS), collect firm-level information about the application of new digital technologies in manufacturing and services. The quality of these data sets makes it possible to empirically test some hypotheses about the determinants and implications of these new technologies. Yet, these surveys consider only European countries, eliminating the possibility to explore the application of ADP technologies in a developing context.

The availability of adequate micro-data on the industrial application of ADP technologies is scarcer in developing and emerging economies. Although some firm-level surveys have been recently conducted, these data collection exercises are country-specific and cannot provide a consistent picture about the diffusion of these technologies across the developing world. For example, Cirera et al. (2021) demonstrate that most local firms in Ceara, a Brazilian state, still rely on pre-digital technologies to perform general business functions and that technology gaps tend to be larger in smaller firms, especially when considering Industry 4.0 technologies. They also present evidence that the main challenge to accelerating technology adoption is lack of firm capabilities. Other studies show similar results for the analysis of countries such as Senegal and Viet Nam (Cirera et al. 2021b, 2021c).

2.2 The "technological generations" approach

In 2019 UNIDO implemented a survey on the adoption of digital production technologies by industrial firms in Ghana, Thailand and Viet Nam (herein: "UNIDO digital adoption survey"). That survey was specifically developed to explore the application of production technologies in manufacturing firms in a developing context, representing one of the first systematic attempts to collect micro-data on the industrial application of ADP technologies in such a context and in a comparative manner, using a standardized survey instrument (Kupfer, Ferraz, and Torracca 2019). The collected information allowed generating a first map of the diffusion of digital production technologies among manufacturing actors in the selected developing and emerging economies in 2019. The main results of the UNIDO digital adoption survey were presented in the UNIDO *Industrial Development Report (IDR) 2020* (see UNIDO 2019).

A distinguishing feature of the UNIDO digital adoption survey is that it did not employ binary questions on specific advanced technologies. Most of the existing surveys on digital technologies undertake a "binary approach", inquiring on the application of specific digital technologies with binary questions.[6] But for highly heterogeneous industrial structures like those of emerging or developing contexts, such a focus on specific technologies presents some relevant shortcomings. First, it disregards the fact that digital solutions have been around for a long time, and that for a firm in a developing context it may be a rational strategic decision to deploy "previous generation" or more obsolete digital technologies. Second, it does not ask firms about other technologies they may have used—even if they were less advanced technologies—thus losing the opportunity to collect information on the level of technological maturity of all surveyed firms. Third, it disregards the fact that the adoption of some specific technologies may be highly associated with the operations sector. Thus, this narrow "binary approach" may not be the most adequate to derive implications for productive and technological policies in a developing context.

[6] For instance, "Does your firm employ 3D printing/cloud computing/big data analytics/Internet of Things?" Yes/No.

To deal with these shortcomings, the UNIDO digital adoption survey embraced a different approach, based on the experience of a firm-level survey implemented in Brazil in 2017 as part of "Industria 2027", an initiative of the Brazilian Industrial Board agency (CNI) and implemented by the Euvaldo Lodi Institute (IEL) , with the technical execution of UNICAMP (Ferraz et al. 2019). This approach considers a range of sets of production technologies possibly employed by manufacturing firms, organizing them as a progression of "technological generations" according to the level of technical and digital sophistication required for their application.

In practice, firms were asked to select one set of technologies among the five groups of technologies, ranging from the simplest ("analog", or generation 0.0) to the most cutting-edge digital technologies ("smart", or generation 4.0), passing through technologies employed in rigid (generation 1.0), lean (generation 2.0) and integrated (generation 3.0) modes of production (Table 2) [7].

Table 2: Technological generations

Technological generation		**Definition**
G 0.0	Zero generation: Analog production	No digital technologies are used throughout the whole production process (such as personal contact with suppliers or via phone, use of machinery that is not micro-electronic based)
G 1.0	First generation: Rigid production	The use of digital technologies is limited to a specific purpose in a specific function and activity (for example, the use of CAD only in product development or use of non-integrated machines operating in isolation)
G 2.0	Second generation: Lean production	Digital technologies involve and connect different functions and activities within the firm (for example, using CAD-CAM linking up product development and production processes, basic automation)
G 3.0	Third generation: Integrated production	Digital technologies are integrated across different activities and functions, allowing for the interconnection of the whole production process—using Enterprise Resource Planning (ERP) systems, fully "paperless" electronic production control system, industrial and service robots
G 4.0	Fourth generation: Smart production	Digital technologies allow for fully integrated, connected and smart production processes, where information flows across operations and generates real-time feedback to support decision-making processes—for example, digital twins, real-time sensors and machine-to-machine communication, collaborative robots (cobots), management decision-making supported by big data and AI support)

Source: UNIDO (2019) based on Kupfer et al (2019).

[7] Even if it may be imprecise to pair a technological generation with a broad and complex concept such as Industry 4.0, for the purpose of our analysis, we are associating Industry 4.0 with the "smart" technology generation (G 4.0).

In 2020 and 2021 UNIDO promoted and implemented firm-level surveys around the world to assess the impact of the COVID-19 pandemic on manufacturing firms (herein: "UNIDO COVID-19 survey"). Although the main goal of the surveys was to collect information on the observed and expected impact of the COVID-19 pandemic crisis on manufacturing firms in emerging and developing economies, it included a module inquiring about digital production technologies. The collection of firm-level information on digital technologies followed the "technological generations" approach employed by the UNIDO digital adoption survey. Section 3 reviews the main features of the UNIDO COVID-19 survey as well as the collected data sample.

3 Data: The UNIDO COVID-19 survey

Between November 2020 and June 2021, UNIDO implemented a firm-level survey in 26 countries in Asia, Africa and Latin America, collecting information from about 3,900 manufacturing firms in operation at the time of the survey (see Annex A for more about the survey and the composition of the full sample). [8]

The survey uses a standardized survey instrument designed by UNIDO and consists of 35-50 questions[9] focusing on the following main dimensions:

- Impact, both observed, since the start of the outbreak, and expected, in the months/years to come, on firms' activities, operations and performance;
- Actions taken to adapt and respond to these current and expected impacts;
- Government measures already implemented and still needed to support manufacturing firms responding to these challenges; and
- General characteristics of the firm, such as size, ownership, sector, international exposure—such as global value chain (GVC) participation, imports and exports—innovation and digitalization.

This paper uses the data collected by the UNIDO COVID-19 survey to empirically test some hypotheses on the determinants of the adoption of ADP technologies as well as on the implications of the COVID-19 pandemic crisis on digitally advanced firms (that is, ADP technologies-adopters). The analysis targets the 3,200 firms that were in operation in manufacturing sectors at the time of the survey. Of this number, 2,700 manufacturing firms that provided valid information on the employed digital production technologies constitute the final sample for the empirical analysis.

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[8] Although they were not the main target of the survey, 658 firms not operating in manufacturing sectors also participated in the survey. These have not been considered in the presented analysis.

[9] Length of the questionnaire can differ from firm to firm because it contains logical jumps (questions based on specific answers to previous questions).

4 Variables and hypotheses

4.1 Assessing the digitalization level of firms

The UNIDO COVID-19 survey follows the "technological generations" approach described earlier, asking firms to identify the set of technologies that best represent the technologies in use in two business functions of the firm: production processes and customer relations (see Table 3).

Table 3: Digitalization profile of UNIDO COVID-19 survey participants

Technological generation	Which of the following set of technologies is currently used by the firm to support the production processes?	Which of the following technologies are used by the firm to support relationships with customers?
G 0.0: Analog	**Analog systems:** Use of machinery that is not micro-electronic based	**Analog systems**: Use of phone, fax or personal contacts
G 1.0: Rigid	**Simple and rigid automation systems:** Use of non-integrated CNC (computer numerical control) machines and/or other non-connected, stand-alone, non-integrated machines operating in isolation	**Manual electronic handling of accounts and contact**s: By electronic means but in an unstructured electronic format (with e-mail and e-mail attachments); client registration and transaction information are dispersed
G 2.0: Lean	**Full or partial automation systems**: Manufacturing processes controlled by PLC (programmable logic controller); use of robots	**Sales force automation:** Use of CRM (customer relationship management) solutions; existence of a client electronic database with account and contact records
G 3.0: Integrated	**Computerized manufacturing execution systems**: Use of MES (manufacturing execution system), AGV (automated guided vehicle), product identification solutions—for example, radio frequency identification (RFID) or QR Code—fully electronic production control systems or mobile production control solutions (such as those that monitor production with mobile devices)	**Web-based integrated support systems:** Use of CRM (customer Relationship Management) solutions with multichannel integration; mobile solutions and salesforce support with mobile apps; web-based Internet sale system; social media integration; customer data analytics
G 4.0: Smart	**Smart production systems:** use of machine-to-machine communication or other systems based on data exchange between machines and components; use of digital twin technology to model individual products; use of real-time sensors for data acquisition and adjustment; use of co-bots, augmented reality, additive manufacturing, real-time production management, artificial intelligence and/or big data analytics to support the management of production	**Client lifecycle management and control:** use of connected devices for gathering and monitoring product usage data throughout lifecycle (i.e., sensors embedded in products); offer of services based on customer usage patterns (i.e., maintenance); artificial intelligence in customer service (i.e., automatic response); analysis and offer of services with support of artificial intelligence and/or big data analytics

Source: authors' elaboration based on the questionnaire of the UNIDO COVID-19 firm-level survey.

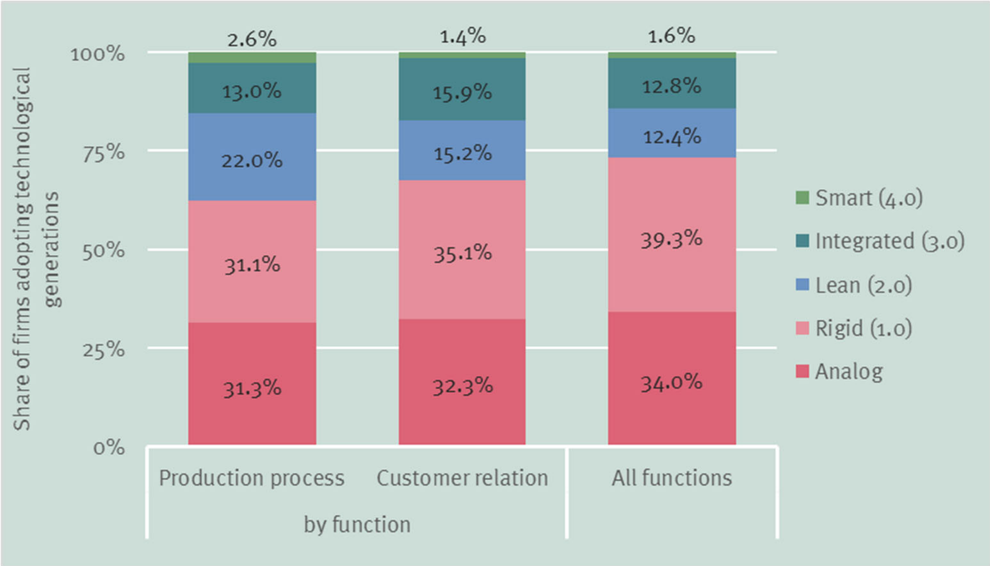
Building on the information provided by these two questions, each firm is associated with one of the five technological generations as a proxy of its level of digitalization. This is done by generating the categorical variable *Production technologies* (PT_i)[10], whose five categories correspond to the five technological generation (1= G 0.0; 2=G 1.0; 3=G 2.0; 4=G 3.0; 5=G 4.0), and that associates each individual firm i with a unique category of the variable PT_i. Using this same information, we also create a dummy variable, *ADP technologies* ($ADPT_i$), which takes the value of 1 when the firm i is associated with a value of PT_i equal to 4 or 5—that is, corresponding to the highest technological generations of "integrated" (G 3.0) and "smart" (G 4.0). Thus, $ADPT_i$ allows us to identify the firms with the most advanced digital profiles; for this reason, we also refer to these firms as "digitally advanced".

The variables PT_i and $ADPT_i$ are the main variables of interest of the presented analysis. These variables not only provide information on the technological and digitalization level of each individual firm. They can also offer a rough idea of the digital gap that exists between firms or within countries and/or regions.

Figure 1 displays the shares of firms associated with the different categories of PT_i in the sample of firms considered for the analysis of this paper. The first two columns show the average technological generations in use in the two business functions of the participating firms, while the third column shows the composition of PT_i. One initial striking finding that emerges is that the diffusion of the most advanced digital technologies—"integrated" (G 3.0) and "smart" (G 4.0)—is still very limited: if taken together, their average rate of adoption is about 14 percent, of which only 1.6 percent corresponds specifically to 4.0 technologies. This finding is in line with what was observed in the UNIDO digital adoption survey (see UNIDO 2019).

[10] See Annex A for more details on the construction of the *Production technologies* (PT_i) variable as an indicator of the diffusion of digital technologies.

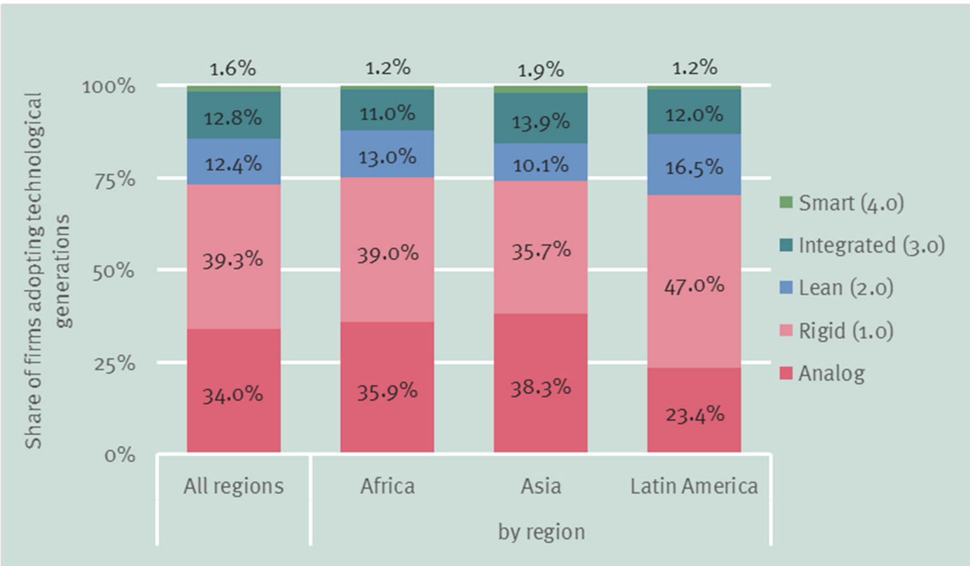
Figure 1: Production technologies (PT) in use during COVID-19 pandemic



Source: Authors' elaboration based on the data collected by the UNIDO COVID-19 firm-level survey.
Note: Sample includes individual firms that were in operation in manufacturing sectors at the time of the survey (N = 2,700).

Figure 2 shows the distribution of PT_i across different world regions.[11] The diffusion of ADP technologies is, on average, around 12 percent in Africa, 13 percent in Latin America and 16 percent in Asia. Asia also displays the largest share of firms associated, on average, with 4.0 technologies (2 percent). It is interesting to note how in Latin America analog production technologies are relatively less diffused than in other regions.

Figure 2: Production technologies (PT) in use during COVID-19 pandemic, by region

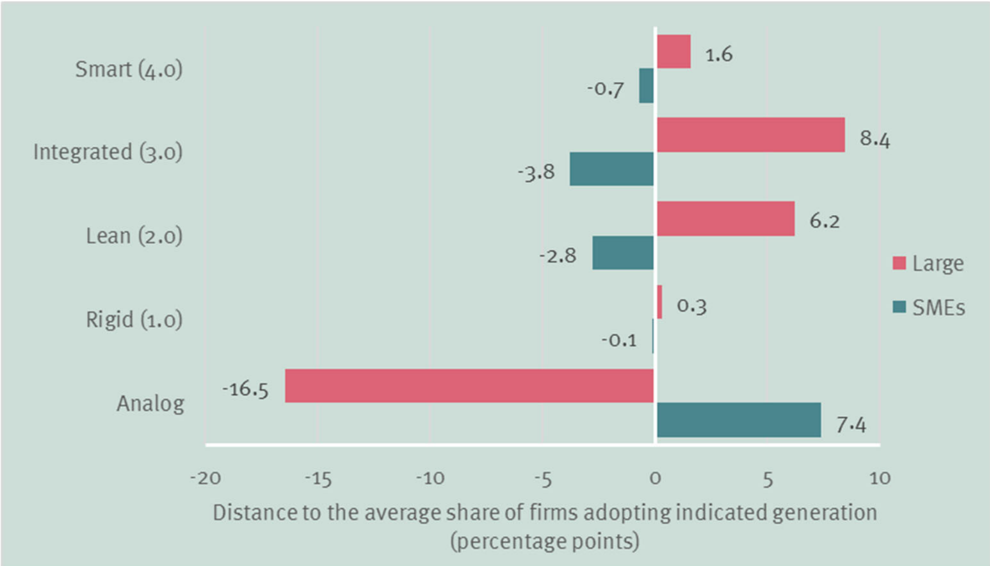


[11] The information by country is presented in Figure B.1 in the annex.

Source: Authors' elaboration based on data collected by the UNIDO COVID-19 firm-level survey.
Note: Sample includes individual firms that were in operation in manufacturing sectors at the time of the survey (N = 2,700, distributed as: Africa = 602; Asia = 1,413; Latin America = 685).

Another interesting feature emerging from the data is the high heterogeneity that exists in the adoption of ADP technologies by firm characteristic. Firm size, for instance, seems to be an important characteristic driving adoption. This is visible in Figure 3, which displays differences in the average adoption of technological generations by firm size.[12] As the data shows, large firms tend to have an above-average rate of adoption in the highest technological generations (3.0 and 4.0), while the opposite is evident for small and medium-sized enterprises (SMEs). This finding is also consistent with the evidence emerging from the UNIDO digital adoption survey (see UNIDO 2019).

Figure 3: Production technology (PT) adoption during the COVID-19 pandemic, by firm size



Source: Authors' elaboration based on data collected by the UNIDO COVID-19 firm-level survey.
Note: SMEs = firms that have up to 99 employees; *Large* = firms that have 100 or more employees. The number of employees is defined as the number of permanent employees reported by the firm at the end of 2019 minus the number of laid-off permanent workers due to the COVID-19 pandemic. Sample includes individual firms that were in operation in manufacturing sectors at the time of the survey (N = 2,700, distributed as: SMEs = 1,865; Large = 835).

Other characteristics are likely to also affect firms' adoption of ADP technologies. One that stands out is firms' production and technological capabilities. To deal with increasingly complex technologies, firms need to develop a broad array of conventional as well as new and increasingly complex capabilities (Andreoni and Anzolin 2019; Bogliacino and Codagnone 2019). Firms endowed with greater capabilities can be better equipped to successfully experiment and apply new technologies (Pietrobelli 1997).

[12] See Table B.1 in Annex B for the composition of the categories of *Production technologies (PT_i)* by firm size.

Based on these arguments, we thus formulate a first hypothesis to be tested in the empirical analysis outlined in Section 5:

Hyp.1: *Firm-level capabilities are positively associated with the probability of adopting ADP technologies, controlling for other factors.*

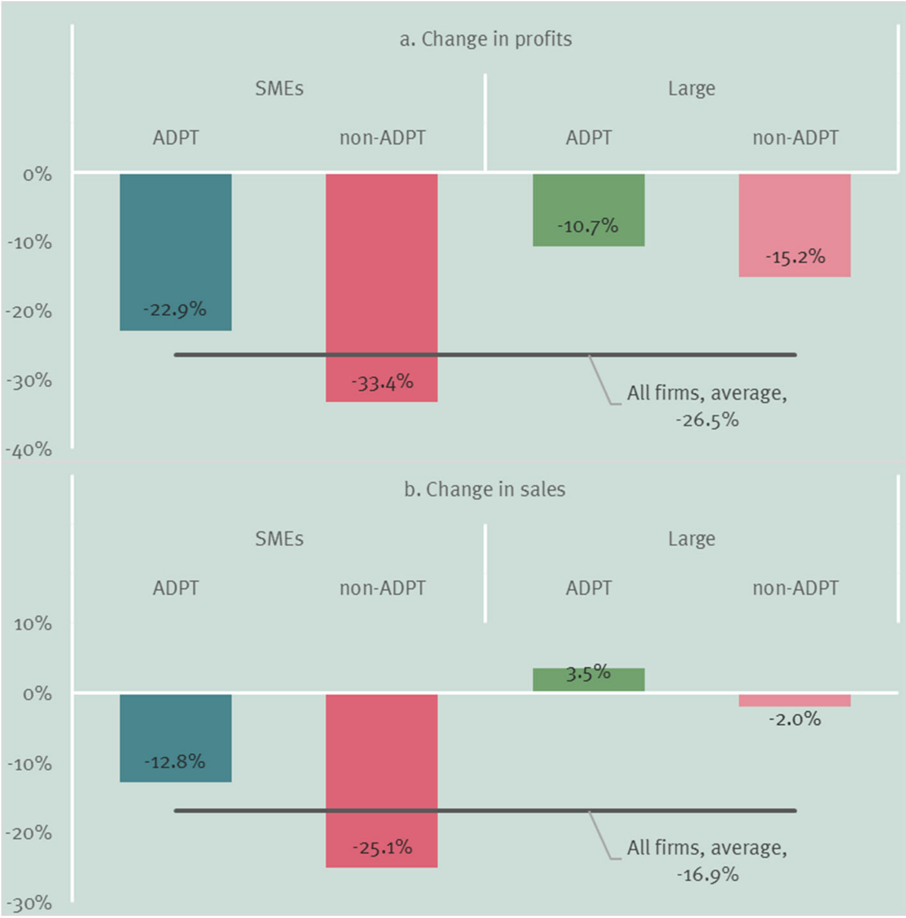
4.2 Quantifying the economic impact of COVID-19

The UNIDO COVID-19 survey allows us to investigate whether some firms were systematically more capable of navigating through the difficult times of the pandemic crisis. In particular, we can assess to what extent the adoption of ADP technologies has been associated with a better performance against the pandemic shock.

The survey captures the impact of the pandemic on manufacturing firms using changes in yearly profits (2020 versus 2019) and in monthly sales (one completed month before the survey was collected against same month 12 months before). While the former indicator provides a synthetic measure of the overall impact of the crisis on the dynamics of the firms in the early phase, the latter can capture eventual changes in the business cycle in line with the different epidemiological waves that countries were facing at the time of data collection.

A first look at the data suggests that digitally advanced firms were, on average, better suited to resist the crisis in terms of impact on both sales and profits. Figure 4 displays firms' average change in yearly profits in 2020 (panel a) and in monthly sales (panel b) compared with the previous year, by their level of digitalization: digitally advanced firms ($ADPT_i$ =1) and the rest ($ADPT_i$ =0). Considering the entire sample, average decline in profits is about 26.5 percent and decline in sales is 19 percent. Both profits and sales dropped more in the case of SMEs than for large firms; but within each firm size category, digitally advanced firms have been able to maintain a better performance than non-digitally advanced ones. In the case of large firms, *ADPT*-adopters actually display positive average changes in monthly sales. Among SMEs, changes in sales and profits of *ADPT*- adopters remains above the average values for all firms, even if they have been affected more severely than large firms.

Figure 4: Changes in profit and sales during the COVID-19 pandemic, by level of digitalization and firm size



Source: Authors' elaboration based on data collected by the UNIDO COVID-19 firm-level survey.
Note: SMEs = small and medium-sized firms that have up to 99 employees; *Large* = firms that have 100 or more employees. The number of employees is defined as the number of permanent employees reported by the firm at the end of 2019 minus the number of laid-off permanent workers due to the COVID-19 pandemic. ADPT = advanced digital production technologies.

These graphical results are confirmed by a *t-test* conducted on the average changes in profits and sales between the two sub-samples: digitally advanced firms vs. non-digitally advanced firms. The *t-test* reported in the furthest right columns of Table 4 shows a significant negative difference, indicating that digitally advanced firms experienced, on average, a lower decline in profits and in sales.[13]

[13] The same results hold when comparing firms of the same size (see Table B.2 in the annex)

Table 4: Summary statistics and t-test: Changes in profits and sales during the COVID-19 pandemic, by level of digitalization

	All firms			*ADPT*=0			*ADPT*=1			*T-test* n differences of averages	
	Obs.	Avg.	SD	Obs.	Av.	SD	Obs.	Av.	SD	Diff	t
Change in profits	2,303	-26.53	41.01	1,968	-28.28	41.04	335	-16.30	39.41	-11.97***	(-4.96)
Change in sales	2,305	-16.86	41.83	1,983	-18.89	42.09	322	-4.38	37.99	-14.51***	(-5.81)

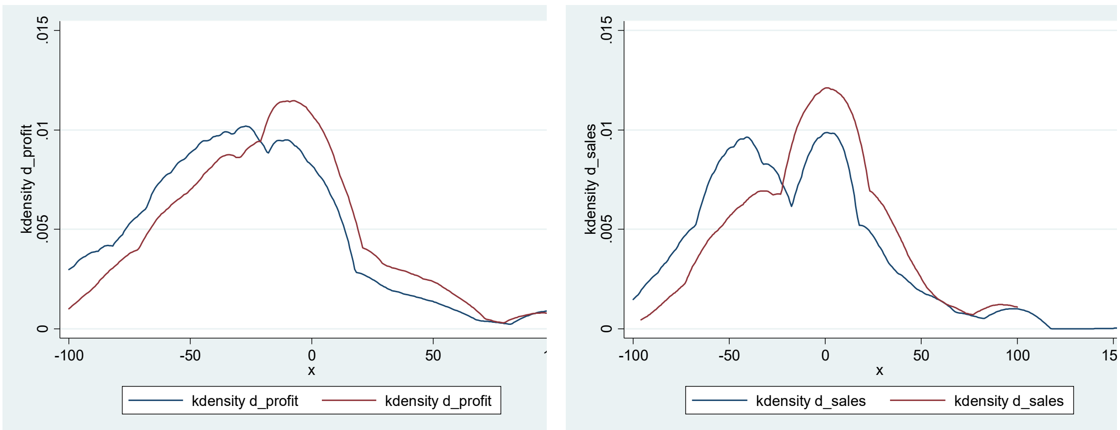
Source: Authors' elaboration based on data collected by the UNIDO COVID-19 firm-level survey.

Note: See Table B.2 in Appendix B for descriptive statistics and the t-test by firm size category. SD = standard deviation: ADPT = advanced digital production technologies.

Further evidence of this difference is apparent when comparing the distributions of changes in profits and sales between digitally advanced and non-digitally advanced firms (see Figure 5). The distribution of digitally advanced firms stochastically dominates the curve of non-*ADPT* adopters, suggesting a systematic difference in the impact of the pandemic (in terms of percentage change in sales and profits) between digitally advanced and non-digitally advanced firms.

Figure 5: Distribution of changes in profits and sales during the COVID-19 pandemic, by level of digitalization

a) Change in yearly profits *b) Change in monthly sales*



Source: Authors' elaboration based on the data collected by the UNIDO COVID-19 firm-level survey

Note: SMEs = firms that have up to 99 employees; *Large* = firms that have 100 or more employees. The number of employees is defined as the number of permanent employees reported by the firm at the end of 2019 minus the number of laid-off permanent workers due to the COVID-19 pandemic.

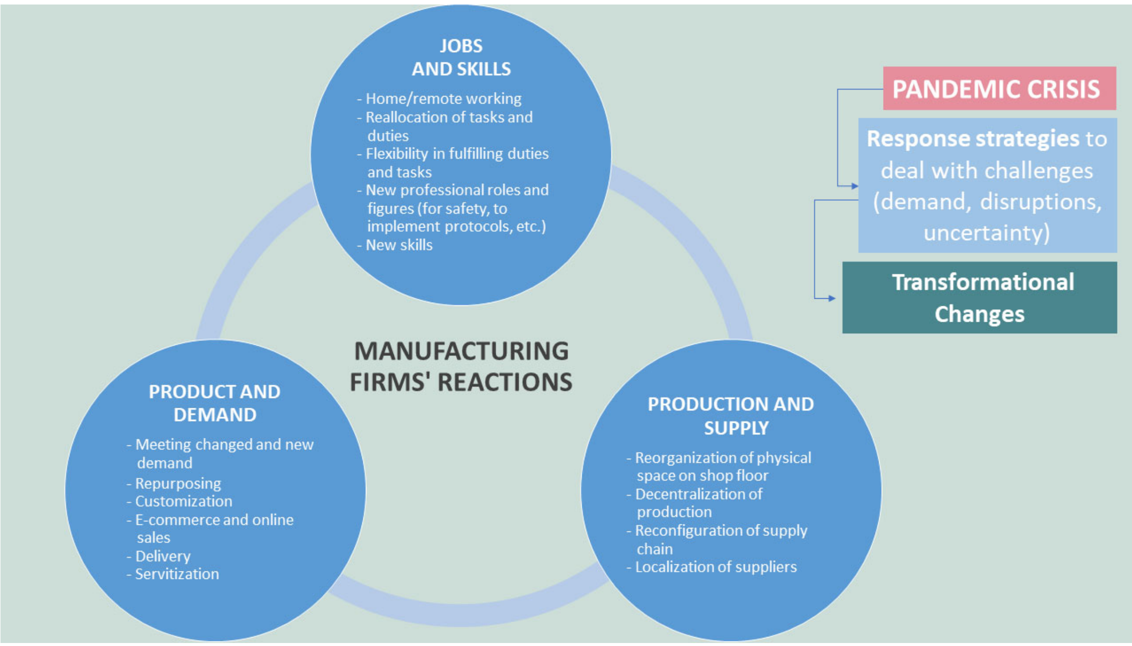
Building on these preliminary findings, we formulate a second hypothesis to be tested in the empirical analysis:

Hyp. 2*: Adoption of advanced digital technologies is positively associated with changes in yearly profits and monthly sales during the COVID-19 pandemic, on average and controlling for other factors.*

4.3 Documenting firm responses to the crisis

Firms are not simply passively affected by an economic crisis; they can also actively respond and react to the challenges eventually posed by the negative shock. In the case of the COVID-19 pandemic, after the first phase of immediate shock at the outbreak, characterized by a generalized slowdown or complete halt of production, some manufacturing firms began implementing different response strategies. The development of a response strategy implies identifying and adjusting one or more aspects of a firm's activities to cope with the changed scenario and adapt to the "new normal" emerging from the pandemic. In practice, this entails introducing one or more direct *transformational changes* into firm operations and routines. Figure 6 classifies the range of possible response strategies, across three broad dimensions: (1) jobs and skills; (2) product and demand; and (3) production and supply.

Figure 6: Responding to the crisis: Transformational changes as response strategies



Source: Authors' elaboration.

The UNIDO COVID-19 survey collected unique information on the response strategies undertaken by manufacturing firms by inquiring about the transformational changes introduced as reaction to the COVID-19 pandemic. Firms were asked to select one or more of the following options:[14]

- *Business activity online*: started or increased business activity online, and/or change in delivery of carry-out of goods or services (for example, online sales, new delivery modes, new distribution channels);
- *Organizational changes*: introduced organizational changes to fulfil new health and safety requirements (for example, change in remote work arrangements, new protocols or standards, new professional roles to supervise health and safety measures);
- *New equipment:* introduced new equipment to reduce the numbers of workers needed on the shop floor (for instance, through the automation of some production processes);
- *Repurposing*: converted, partially or fully, production to address the health emergency (for instance, producing medical equipment, masks, sanitizer);
- *New product*: released new products to meet changes in demand;
- *No change was introduced.*

Most of the transformational changes listed in the survey are classified under the "product and demand" and "production and supply" dimensions presented in Figure 6, but some also overlap with the "jobs and skills" dimension (such as change to remote work or organizational changes to fulfil health and safety requirements).

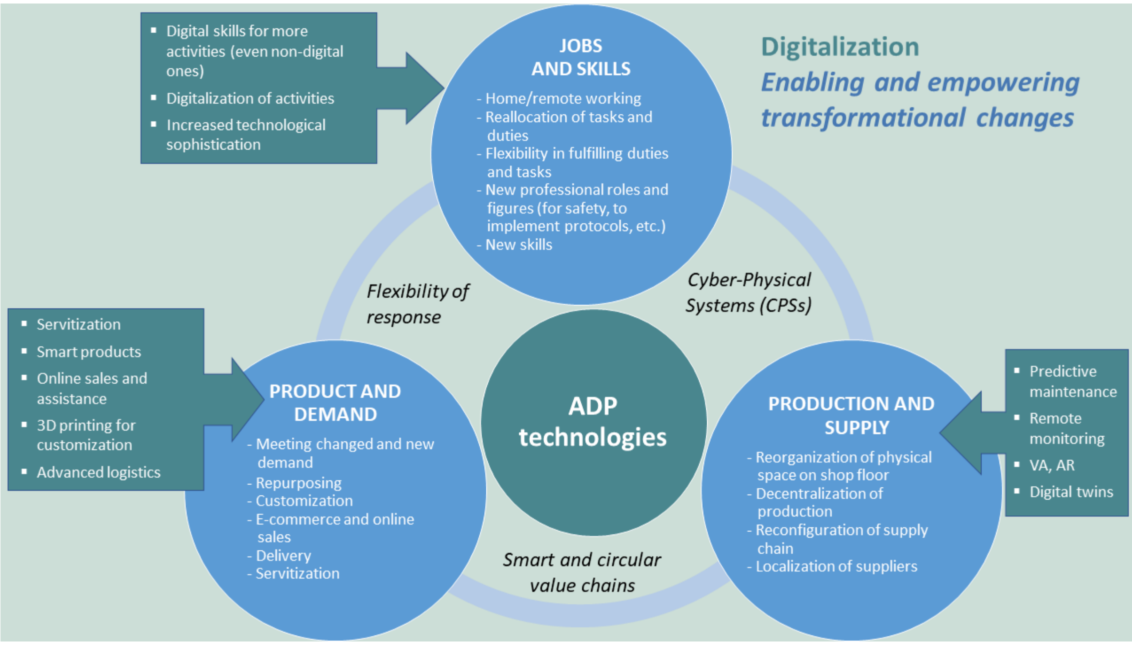
More than 60 percent of surveyed firms introduced some organizational changes to fulfil new health and safety requirements, and almost 40 percent increased their business activity online. It is not surprising that these transformational changes have been more popular than more financially and operationally demanding changes, such as developing new products and—perhaps even more onerous—introducing new equipment, which were introduced, on average, by about 30 and 20 percent of surveyed firms, respectively.

Digitalization may play a critical role in facilitating the adoption of response strategies. For example, a workforce with digital competencies may find it easier to shift to remote work when possible; or, familiarity with the industrial application of ADP technologies may facilitate the reorganization of production processes to accommodate safety measures and enable social distancing. Figure 7 provides concrete examples of how the

[14] The original survey questionnaire asks the question "Did the firm experience any of the following changes in response to the COVID-19 outbreak?", listing the following transformational changes as possible answer options: change in business activity online; change in delivery or carry-out of goods or services; change in remote work arrangement; introduced new equipment; repurposing; released new products; introduced organizational changes; other changes; no changes introduced. For the analysis presented in this paper, some of these changes have been consolidated based on the type of operations and business functions involved. Change in business activity online and change in delivery or carry-out of goods or services are combined, as both are associated with customer relationships through online sales and delivery. In addition, remote work arrangement is combined with organizational changes.

application of ADP technologies may facilitate the introduction of transformational changes.

Figure 7. Effect of digitalization on the implementation of response strategies



Source: Authors' elaboration.

Note: ADP = advanced digital production; VR = virtual reality; AR = augmented reality.

One initial approach to examining this relationship consists of looking at the share of firms introducing each change, distinguishing between digitally advanced and non-digitally advanced firms, controlling by their size (see Figure 8). Results indicate that, on average, digitally advanced firms introduced more frequently transformational changes than non-digitally advanced one; and this holds for all transformational changes and firm-size categories. In many cases, the adoption of ADP technologies compensates for the lower rate of introduction of transformational changes typically observed in SMEs relative to large firms.

Figure 8. Transformational changes introduced during the COVID-19 pandemic, by level of digitalization and firm size

Source: Authors' elaboration based on data collected by the UNIDO COVID-19 firm-level survey.

Note: SMEs = small and medium-sized firms that have up to 99 employees; *Large* = firms that have 100 or more employees. The number of employees is defined as the number of permanent employees reported by the firm at the end of 2019 minus the number of laid-off permanent workers due to the COVID-19 pandemic. ADPT = advanced digital production technologies.

The results are confirmed by a *t-test* to compare the average share of digitally advanced firms introducing each change to that of non-digitally advanced firms (see Table 5). The difference between the share of firms introducing transformational changes is significant across all changes listed. It is also interesting to note that the share of digitally advanced firms not implementing any change is significantly lower than the share of non-digitally advanced firms.[15]

[15] The same results hold when comparing firms of the same size (see Table B.3 in the annex)

Table 5: Summary statistics and t-test: Transformational changes, by level of digitalization

	All firms			ADPT==0			ADPT==1			T-test n differences in averages	
	Obs.	Avg.	SD	Obs.	Avg.	SD	Obs.	Avg.	SD	diff	T
Business activity online	2,700	0.37	0.48	2,313	0.35	0.48	387	0.48	0.50	-0.127***	(-4.80)
Organizational change	2,700	0.64	0.48	2,313	0.63	0.48	387	0.75	0.43	-0.125***	(-4.79)
New equipment	2,700	0.21	0.40	2,313	0.19	0.39	387	0.32	0.47	-0.138***	(-6.24)
Repurposing	2,700	0.22	0.41	2,313	0.21	0.41	387	0.28	0.45	-0.0741**	(-3.27)
New product	2,700	0.30	0.46	2,313	0.28	0.45	387	0.39	0.49	-0.109***	(-4.36)
No change	2,700	0.15	0.35	2,313	0.16	0.37	387	0.07	0.26	0.0850***	(4.38)

Source: Authors' elaboration based on the data collected by the UNIDO COVID-19 firm-level survey.

Note: See Table B.2 in Annex B for more details on the descriptive statistics and the t-test by firm size category. ADPT = advanced digital production technologies; SD = standard deviation.

Building on these finding, we formulate a third hypothesis to be tested in the empirical analysis:

Hyp. 3*: ADP technology adoption is positively associated with the introduction of transformational changes in response to the COVID-19 pandemic, on average and controlling for other factors.*

4.4 Summary of variables used

Table 6 presents the description and the basic summary statistics of the variables considered for the empirical analysis.

Table 6: Firm characteristics: Definitions and summary statistics

Variable	Obs.	Avg.	SD	Min	Max	Definition
Production technologies:						
Analog	2,700	0.34	0.47	0	1	Dummy equals 1 if the firm employs production technologies associated with the analog (G 0.0) technological generation.
Rigid	2,700	0.39	0.49	0	1	Dummy equals 1 if the firm employs production technologies associated with the rigid (G 1.0) technological generation.
Lean	2,700	0.12	0.33	0	1	Dummy equals 1 if the firm employs production technologies associated with the lean (G 2.0) technological generation.
ADPT	2,700	0.14	0.35	0	1	Dummy equals 1 if the firm employs production technologies associated with the integrated (G 3.0) or smart (G 4.0) generations.
Impact of COVID-19 pandemic:						
Change in profits	2,303	-26.53	41.01	-100	100	Percentage change in the value of yearly profits in 2020 with respect to the value of yearly profits in 2019.
Change in sales	2,305	-16.86	41.83	-100	157	Percentage change in the value of monthly sales completed one month before the survey was collected with respect to the value of monthly sales in the same month one year before.
Transformational changes:						
Business activity online	2,700	0.37	0.48	0	1	Dummy equals 1 if the firm started or increased business activity online, and/or change in delivery of carry-out of goods or services (for example, online sales, new delivery modes, new distribution channels).
Organizational change	2,700	0.64	0.48	0	1	Dummy equals 1 if the firm introduced organizational changes to fulfil new health and safety requirements (for example, change in remote work arrangements, new protocols or standards, new professional roles to supervise health and safety measures).
New equipment	2,700	0.21	0.40	0	1	Dummy equals 1 if the firm introduced new equipment to reduce the numbers of workers needed on the shop floor (for instance, through the automation of some production processes).
Repurposing	2,700	0.22	0.41	0	1	Dummy equals 1 if the firm converted, partially or fully, production to address the health emergency (for instance, producing medical equipment, masks, sanitizers).
New product	2,700	0.30	0.46	0	1	Dummy equals 1 if the firm released new products to meet changes in demand.
No change	2,700	0.15	0.35	0	1	Dummy equals 1 if the firm did not introduce any type of transformational change.
Employment:						
Total	2,700	316.38	2,071	1	73,200	Total employment, measured by the number of permanent employees plus the number of temporary employees, weighted by 0.6.
Total (log)	2,700	4.12	1.61	0	11.2	Total employment as defined above, in log.
Total (log), squared	2,700	19.53	14.74	0	125.5	Total employment as defined above, squared.
Innovation:						
Process innovation	2,700	0.38	0.49	0	1	Dummy equals 1 if the firm introduced a new process between 2018 and end of 2019.
Product innovation	2,700	0.54	0.50	0	1	Dummy equals 1 if the firm introduced a new or a significantly improved product between 2018 and the end of 2019.
Organizational innovation	2,700	0.28	0.45	0	1	Dummy equals 1 if the firm introduced a new organizational method between 2018 and the end of 2019.
Investment in new software	2,700	0.27	0.45	0	1	Dummy equals 1 if the firm invested in a new software between 2018 and the end of 2019.
GVC	2,524	0.27	0.44	0	1	Dummy equals 1 if the firm participated in a global value chain in 2019.
Export	2,689	0.24	0.43	0	1	Dummy equals 1 if the firm's share of sales/turnover exported abroad in 2019 was more than 30 percent of total sales/turnover in 2019.
Ownership:						
Private firm (non-foreign invested)	2,699	0.79	0.41	0	1	Dummy equals 1 if the firm is a privately-owned domestic firm with no foreign ownership.
Foreign invested	2,699	0.17	0.37	0	1	Dummy equals 1 if the firm is a privately-owned firm with foreign ownership.
State-owned and other	2,699	0.04	0.20	0	1	Dummy equals 1 if the firm is state-owned or another type of ownership (not included in the ones above).

Source: Authors' elaboration based on the data collected by the UNIDO COVID-19 firm-level survey.

Note: See Table B.4 in Annex B for the descriptive statistics and details on the t-test by firm size category. ADPT = advanced digital production technologies; GVC = global value chain; SD = standard deviation.

5 Empirical approach

5.1 Modelling the adoption of digital technologies (Hyp.1)

To empirically test the first hypothesis (Hyp.1) we proceed in two steps. First, considering the binary nature of the variable capturing the adoption of most advanced digital technologies ($ADPT_i$), we implement a probability model where ADP technology adoption is a latent variable:

$$\Pr(ADPT_i = 1) = \beta_0 + \beta_1 x_i + \beta_2 c_i + \beta_3 s_i + \varepsilon_i \quad (1)$$

where $ADPT_i$ is a binary variable that takes the value of 1 if the firm is associated with "integrated" (G 3.0) or "smart" (G 4.0) technological levels, and 0 otherwise; x_i is a vector of firm-level variables; c_i and s_i refer to, respectively, country- and sector-fixed effects; and ε_i is the normally distributed error term. To estimate equation (1), we implement a probit model with robust standard errors.

The vector x_i contains general firm-level characteristics, such as firm size—proxied by the number of employees—and type of ownership. The empirical literature is nearly unanimous in recognizing that large firms may find it easier to experiment and adopt new technological solutions, which tend to be more risky and costly than mature technologies, due to their fewer financial constraints (Fabiani, Schivardi, and Trento 2005). Similarly, foreign-owned firms have been found to be early adopters of new technologies (Gómez and Vargas 2012), since international exposure can serve as a channel for knowledge diffusion for manufacturing firms operating in developing and emerging industrial economies (Morrison, Pietrobelli, and Rabellotti 2008; Saliola and Zanfei 2009) and for learning about the industrial application of new digital production technologies(Zanello et al. 2016; Delera et al. 2022). Hence, to account for the fact that firms integrated in these international networks could be more prone to adopt new technologies, the vector x_i also contains variables related to export (*Export)* and participation in production networks such as global value chains (*GVC*).

Firm-level capabilities are necessary to learn, operate and integrate new technologies in production. Moving upwards along the ladder of digitalization requires an upgrade in terms of different capabilities. These include not only technological capabilities but also production and organizational ones (UNIDO 2019). To proxy for these capabilities, we follow the empirical literature and include covariates accounting for the introduction of technological innovation between 2018 and the end of 2019 (*Product innovation* and *Process innovation*). To account for the organizational learning needed to integrate and retrofit new technologies in production processes, we introduce a variable for introducing organizational changes between 2018 and the end of 2019 (*Organizational innovation*). Finally, acknowledging that the adoption of advanced digital technologies relies on the acquisition of digital capabilities related to the development and use of software, we also include a variable accounting for past investments (by end 2019) in new software. Estimated coefficients for the capability-related variables included, which are positive and statistically significant, would be taken as evidence supporting Hyp.1.

As a second step, we exploit the categorical nature of the information of adopted production technologies and estimate an ordered probit model using, as dependent variable, the categorial variable *PT_ADPT*$_i$, derived from *PT*$_i$ and whose categories are ranked by an ordinal scale. To obtain *PT_ADPT*$_i$, we follow Delera et al. (2022) and sum the two highest categories of *PT*$_i$ (corresponding to "integrated" 3.0 and "smart" 4.0 technologies, thus to *ADPT*$_i$). The corresponding latent variable can still be thought as a metric of the technological progress: firms belonging to the two extremes of the spectrum are, respectively, firms relying predominantly on analog technology and firms relying predominantly on advanced digital technologies. Ordered models identify a number of cut points, which partition this function into a series of regions. Considering each of the four categories of *PT_ADPT*$_i$, we observe falls within one region. We are therefore estimating the likelihood that a firm would fall into a higher (or lower) region—corresponding to a given level of technological competence—as a function of rank and epidemic effects. We proxy these effects using the same set of variables used in our probit model.

5.2 Modelling pandemic effects in terms of changes in sales and profits (Hyp.2)

To empirically test the second hypothesis (Hyp. 2), we make use of the information on changes in profits and sales to explore the relationship between the adoption of ADP technologies and the severity of the impact of the pandemic on firms. The following model is estimated using ordinary least squares (OLS) techniques:

$$Change\ (profits\ or\ sales_i) = \beta_0 + \beta_1 x_i + \beta_2 ADPT_i + \beta_3 c_i + \beta_4 s_i + \varepsilon_i \quad (2)$$

where $Change\ (profits\ or\ sales_i)$ is a continuous variable representing the change in profits or sales of firm *i; ADPT*$_i$ is the main independent variable; x_i is a vector of firm-level variables; c_i and s_i refer to, respectively, country- and sector-fixed effects; ε_i is the normally distributed error term; and the vector x_i includes the same variables used to test Hyp.1—that is, technological and organizational innovation, past investments in software, and variables related to insertion in international production and trade networks (*GVC* and *Export*). An estimated coefficient β_2 positive and statistically significant would be taken as evidence supporting Hyp.2.

5.3 Modelling pandemic response strategies in terms of introduction of transformational changes (Hyp.3)

To empirically test the third hypothesis (Hyp. 3) we estimate probability models for each of the five transformational changes, where the introductions of the transformational change are taken as latent variables:

$$\Pr(TC_i = 1) = \beta_0 + \beta_1 x_i + \beta_2 ADPT_i + \beta_3 c_i + \beta_4 s_i + \varepsilon_i \quad (3)$$

where *TC*$_i$ is a binary variable that takes the value of 1 if a firm has introduced the transformational change, 0 otherwise; *ADPT*$_i$ is the main independent variable; x_i is the vector of firm-level variables; c_i and s_i refer to, respectively, country- and sector-fixed effects; ε_i is the normally distributed error term; and x_i includes the same variables used in the models for equations (1) and (2). Including x_i, c_i and s_i as controls, we estimate equation (3) with a probit model. Estimated coefficients β_2 positive and statistically significant would be taken as evidence supporting Hyp.3.

6 Results and discussion

6.1 Drivers of ADP technology adoption

Table 7 presents the results of the probit model detailed in equation 1. In line with the existing literature, technological innovation is significantly and positively correlated with the adoption of ADP technologies. In particular, having introduced a process innovation is associated with a significant higher likelihood (about 5 percentage points) of having adopted ADP technologies. Moreover, as expected, results confirm the positive correlation between investments in software and the adoption of ADP technologies. Past introduction of organizational innovations, instead, does not seem to have a significant impact on the likelihood of adopting ADP technologies.

In line with the results reported in Delera et al. (2022), participation in GVCs is positive and significantly associated with ADP technology adoption. In the considered sample, the effect of being integrated in a GVC is larger and more significant than being an exporter outside GVCs, which is positive but not significant. Foreign ownership is also positive and significantly associated with ADP technology adoption. As expected, firm size (proxied by total employment) is also positively and significantly associated with the adoption of these technologies.

Table 7: Drivers of ADP technology adoption: Marginal effects

Dependent variable: ADPT	(1)	(2)
Process innovation	0.050***	0.049***
	(0.013)	(0.014)
Product innovation	0.025*	0.028**
	(0.013)	(0.014)
Organizational innovation	0.011	0.002
	(0.015)	(0.015)
Total employment (log)	0.026***	0.023***
	(0.005)	(0.005)
Ownership: foreign invested	0.058***	0.054***
	(0.017)	(0.018)
Ownership: state-owned and other	0.050*	0.047
	(0.030)	(0.030)
Investment in new software	0.056***	0.053***
	(0.014)	(0.015)
GVC		0.037**
		(0.015)
Export (above 30% sales)		0.023
		(0.016)
Sector	Yes	Yes
Country	Yes	Yes
Obs.	2,699	2,514

Source: Authors' elaboration based on the data collected by the UNIDO COVID-19 firm-level survey.

Note: The base category for ownership is *Private firm (non-foreign invested)*. For probit coefficients, see Table C.1 in Annex C. Standard errors in parentheses: *p<0.10; **p<0.05; ***p<0.01. ADPT = advanced digital production technology; GVC = global value chain.

Further evidence of the drivers of ADP technology adoption is provided in Table 8, which reports the results of the ordered probit model that uses the categorical variable derived from PT_ADPT_i. The marginal effects of the covariates are as expected and consistent with the findings of the probit model: whereas they have a negative sign on the likelihood of adopting analog technologies, they have a positive effect on the adoption of all levels of digital technologies. Moreover, the variable *Organizational innovation* displays a significant coefficient. The coefficient as well as all marginal effect of *Export* remain non-significant.

Table 8: Drivers of production technologies: Oprobit coefficients and marginal effects

Dependent variable: Production technologies (4 categories)	(1)	(2)	(3)	(4)	(5)
	Oprobit coeff.	Oprobit marginal effects			
		Analog	Rigid	Lean	ADP
Process innovation	0.180***	-0.059***	0.008***	0.016***	0.036***
	(0.049)	(0.016)	(0.002)	(0.004)	(0.010)
Product innovation	0.218***	-0.072***	0.009***	0.019***	0.043***
	(0.048)	(0.016)	(0.003)	(0.004)	(0.010)
Organizational innovation	0.141***	-0.046***	0.006**	0.012***	0.028***
	(0.052)	(0.017)	(0.002)	(0.005)	(0.010)
Investment in new software	0.246***	-0.081***	0.011***	0.022***	0.049***
	(0.053)	(0.017)	(0.003)	(0.005)	(0.011)
GVC	0.190***	-0.062***	0.008***	0.017***	0.038***
	(0.055)	(0.018)	(0.003)	(0.005)	(0.011)
Export (above 30% sales)	-0.012	0.004	-0.001	-0.001	-0.002
	(0.059)	(0.019)	(0.003)	(0.005)	(0.012)
Total employment (log)	0.154***	-0.051***	0.007***	0.014***	0.030***
	(0.018)	(0.006)	(0.001)	(0.002)	(0.004)
Ownership: foreign invested	0.258***	-0.085***	0.011***	0.023***	0.051***
	(0.068)	(0.022)	(0.003)	(0.006)	(0.013)
Ownership: state-owned and other	0.156	-0.051	0.007	0.014	0.031
	(0.122)	(0.040)	(0.005)	(0.011)	(0.024)
cut1	0.559***				
	(0.158)				
cut2	1.711***				
	(0.161)				
cut3	2.201***				
	(0.163)				
Sector	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes
Obs.	2,514	2,514	2,514	2,514	2,514

Source: Authors' elaboration based on the data collected by the UNIDO COVID-19 firm-level survey.

Note: The base category for ownership is *Private firm (non-foreign invested)*. Standard errors in parentheses: *p<0.10; **<0.05; ***p<0.01. ADP = advanced digital production; GVC = global value chain.

The results presented in this section therefore provide empirical evidence in support of the first hypothesis (Hyp.1): firm-level capabilities are positively associated with the likelihood of having adopted the most advanced digital technologies, even after controlling for other potentially relevant factors.

6.2 Impact of COVID-19 and advanced digitalization

Results of the OLS models estimating the changes in profits and sales (see equation 2) are reported in Table 9. ADP technology adoption is positively and significantly associated with both changes in yearly profits—columns (1) and (2)—and changes in monthly sales—columns (3) and (4). This suggests that during the COVID-19 pandemic, digitally advanced firms were able to enjoy a "performance premium" (in the form of an increase or a lower decline in sales and profits) compared to non-digitally advanced firms. Variables associated with firms' technological and production capabilities have positive coefficients, but they are not statistically significant. One reason for this finding could be that their effect is already indirectly captured in the variable $ADPT_i$—of which these factors have been found to be significant drivers.

Looking at the other covariates, we find a significant non-linear relationship between changes in sales or profits and number of employees, suggesting a positive but decreasing effect of firm size. The results of the variables related to integration in GVCs are more puzzling. Foreign-invested firms enjoy an advantage in sales and profits performance over private non-foreign invested ones. However, the coefficient of *GVC* is significant (at 10 percent) only in the case of changes in sales, while it turns non-significant in the case of changes in profits once other capabilities-related variables are included. The coefficient of *Export* is significant but negative, thus supporting the argument that the pandemic may have hit actors relying on foreign markets and international trade flows harder.

Table 9: Determinants of changes in profits and sales

Dependent variable	Change in profits		Change in sales	
	(1)	(2)	(3)	(4)
ADPT	**5.887****	**5.626****	**6.030****	**5.482****
	(2.429)	**(2.446)**	**(2.417)**	**(2.435)**
Total employment (log)	-5.241**	-5.433**	-4.660**	-5.035**
	(2.328)	(2.336)	(2.221)	(2.226)
Total employment (log), squared	0.869***	0.877***	0.969***	0.989***
	(0.249)	(0.250)	(0.240)	(0.240)
Ownership: foreign invested	7.216***	7.395***	8.938***	9.279***
	(2.456)	(2.463)	(2.430)	(2.434)
Ownership: state-owned and other	9.549**	9.568**	5.261	5.326
	(4.188)	(4.193)	(4.134)	(4.134)
GVC	3.563*	3.132	4.306**	3.450*
	(1.973)	(2.004)	(1.952)	(1.981)
Export (above 30% sales)	-6.236***	-6.225***	-7.229***	-7.173***
	(2.099)	(2.103)	(2.072)	(2.073)
Process innovation		1.047		2.857
		(1.762)		(1.737)
Product innovation		0.254		0.991
		(1.770)		(1.755)
Organizational innovation		1.577		2.365
		(1.937)		(1.908)
Investment in new software		0.989		0.985
		(1.955)		(1.951)
Constant	-38.111***	-38.559***	-15.506**	-16.968**
	(7.463)	(7.530)	(6.998)	(7.051)
Sector	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes
Obs.	2,157	2,157	2,260	2,260
Degrees of freedom	52	56	52	56
Radj	0.16	0.16	0.17	0.17

Source: Authors' elaboration based on the data collected by the UNIDO COVID-19 firm-level survey.

Note: The base category for ownership is *Private firm (non-foreign invested)*. Standard errors in parentheses: *p<0.10; **p<0.05; ***p<0.01. ADPT = advanced digital production technologies; GVC = global value chain.

The results of the OLS estimations provide empirical evidence in support of the second hypothesis (Hyp.2): changes in yearly profits and monthly sales during the COVID-19 pandemic are positively associated with having adopted ADP technologies, even after controlling for other factors affecting firms' performance.

6.3 Responses to the COVID-19 pandemic and digitalization

To look at the factors affecting the introduction of transformational changes, we implemented five separate probit models following equation 3. The results are reported in Table 10. As shown in the first row of the table, ADP technology adoption is positively and significantly associated with the introduction of each transformational change: digitally advanced firms are more likely than non-digitally firm to increase their business activity online (by almost 10 percentage points), to implement an organizational change to fulfil health and safety requirements (by almost 6 percentage points), to introduce new equipment to reduce the number of workers on the shop floor and increase distancing (by almost 7 percentage points), to repurpose production (by almost 5 percentage points), and to introduce a new product to meet changes in demand (by almost 7 percentage points). Figure 9 summarizes these results by displaying the coefficients of $ADPT_i$ obtained by the five probit models.

With few exceptions, the variables associated with firms' technological and production capabilities have positive and significant coefficients. The fact that $ADPT_i$ maintains a significant effect even when controlling for these factors suggests that these capabilities facilitated the development and implementation of a response strategy to the challenges posed by the COVID-19 pandemic and enabled firms to adapt to a "new normal", beyond digital solutions.

Results for the variables related to trade and international production networks are quite heterogeneous across the five models. The coefficient of *GVC* is positive but never significant. This suggests that the variable *GVC* may have different effects on the impact and response to the COVID-19 pandemic: on the one hand, being inserted into a GVC seems to have shielded firms from a more severe decline of profits and sales (see Table 9); on the other hand, it did not seem to make any difference when it comes to help firms react. The coefficient of *Export* is rather unstable across models, but it turns positive and significant in the case of *New equipment.* This suggests that exporting firms attempted to quickly increase their production efficiency as they faced a critical situation in international markets. This interpretation is consistent with the argument that exporting firms were hit more severely by the negative shock associate with the pandemic crisis, as showed also in Table 9 by the negative correlation between export and performance in terms of changes in sales and profits. Interestingly, the effect of employment is also quite heterogeneous: whereas for the transformational changes associate with the introduction of *Organizational change*, *New equipment,* and *Repurposing,* this coefficient is positive and significant, it turns negative and non-significant when the transformational change corresponds to the introduction of a *New product*, and negative and significant in the case of *Business activity online*. The latter result may be explained by the fact that large firms were more likely to conduct already-online activities related to sales and delivery even before the pandemic.

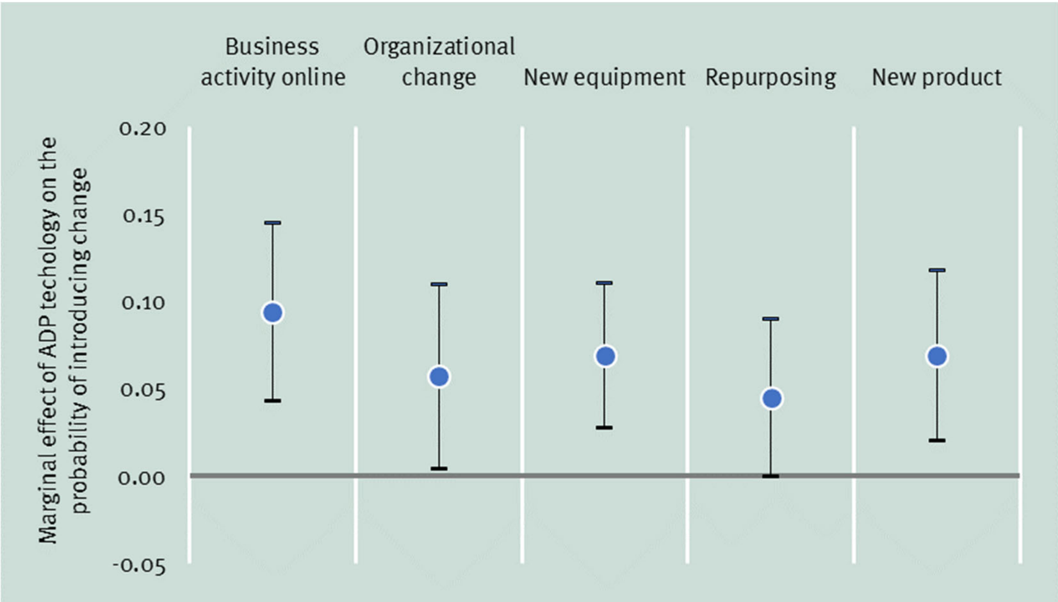
Table 10: Drivers of transformational change: Marginal effects

Dependent variable:	Business activity online	Organizational change	New equipment	Repurposing	New product
	(1)	(2)	(3)	(4)	(5)
ADPT	**0.094***** **(0.026)**	**0.057**** **(0.027)**	**0.069***** **(0.021)**	**0.045**** **(0.023)**	**0.069***** **(0.025)**
Total employment (log)	-0.012* (0.006)	0.047*** (0.007)	0.020*** (0.006)	0.014** (0.006)	-0.004 (0.006)
Product innovation	0.057*** (0.019)	0.079*** (0.018)	0.058*** (0.016)	0.059*** (0.017)	0.185*** (0.018)
Process innovation	0.144*** (0.019)	0.051*** (0.019)	0.081*** (0.016)	0.071*** (0.017)	0.106*** (0.018)
Organizational innovation	0.076*** (0.021)	0.103*** (0.021)	0.029 (0.018)	0.070*** (0.018)	0.045** (0.020)
Investment in new software	0.046** (0.022)	0.066*** (0.022)	0.059*** (0.018)	-0.014 (0.019)	0.036* (0.021)
GVC	0.013 (0.022)	0.035 (0.022)	0.024 (0.018)	0.008 (0.019)	-0.006 (0.021)
Export (above 30% sales)	-0.016 (0.022)	-0.014 (0.022)	0.051*** (0.019)	-0.003 (0.020)	0.011 (0.022)
Ownership: foreign invested	-0.037 (0.027)	-0.005 (0.027)	-0.016 (0.023)	-0.053** (0.024)	-0.071*** (0.027)
Ownership: state-owned and other	0.023 (0.043)	-0.049 (0.044)	-0.039 (0.039)	-0.030 (0.041)	-0.034 (0.043)
Sector	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes
Obs.	2,514	2,514	2,503	2,514	2,514

Source: Authors' elaboration based on the data collected by the UNIDO COVID-19 firm-level survey.

Note: The base category for ownership is *Private firm (non-foreign invested)*. For probit coefficients, see Table C.2 in Annex C. Standard errors in parentheses: *p<0.10; **p<0.05; ***p<0.01. ADPT = advanced digital production technologies; GVC = global value chain.

Figure 9: Drivers of transformational change: Marginal effects of ADPT



Source: Authors' elaboration based on the data collected by the UNIDO COVID-19 firm-level survey.

Hence, the results of the individual probit estimations for the five transformational changes provide empirical evidence in support of the third hypothesis (Hyp.3), that the adoption of advanced digital technologies is positively associated with the introduction of transformational changes in response to the COVID-19 pandemic, on average and after controlling for other potentially relevant factors.

7 Conclusions

Advanced digitalization is becoming one of the key drivers of industrial competitiveness. On the shop floor, machine-to-machine communications, supported by big data analytics and machine learning, are boosting productivity, improving capital utilization and reducing operational cost. Outside the factory, these technologies are increasingly supporting supply-chain coordination, logistics and the interaction with final consumers. Firms, and countries that manage to master and absorb these technologies, are already benefiting from competitiveness premiums.

Despite these potential benefits, little is known about the diffusion and actual impact of ADP technologies in the context of developing and emerging industrial economies due to the lack of cross-country comparable data. This paper aims to fill some of these gaps, making use of a novel data set collected by UNIDO and partners during 2020 and 2021 on manufacturing firms around the world.

The results of the paper show that the diffusion of ADP technologies in manufacturing firms in developing countries is still limited to a few cutting-edge leading firms, typically large and well-integrated in global production networks. The vast majority of firms analysed are, instead, operating very far from the technological frontier, using outdated digital technologies or no digital technologies at all. Addressing this digital gap is a top policy priority that needs to be tackled if countries are to succeed in the future landscape of industrial development.

The results also point towards some important factors that can facilitate the adoption of these technologies. Among them, technology and production capabilities stand out, stressing once again the fundamental role that capability-building should play in industrial and technological policies that are oriented to reduce this digital gap and helping countries catch up with the world frontier.

During the COVID-19 pandemic, digitalization has been regarded as a prime factor of resilience for manufacturing firms. Digital technologies facilitated the shift towards tele-working required by the lock-downs measures needed to contain the virus. They also enabled firms to keep customers even when the retail sector was fully or partially shut down. In demonstrating that firms coped with and reacted to the COVID-19 pandemic crisis on the basis of their capabilities, this paper highlights the importance of digitalization in strengthening industrial resilience and helping firms be better prepared for the post-pandemic future. The analysis confirms the crucial role that ADP technologies have played in supporting firms' reactions to the pandemic in the context of developing and emerging industrial economies. Not only have digitally advanced firms suffered less, on average, during the crisis. They have also been more likely to proactively react to the crisis by introducing transformational changes in their operations. In the years to come, digitalization might be not only a source of competitiveness but also a source of resilience to extreme events like the COVID-19 pandemic.

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Annex A: UNIDO survey on the impact of the COVID-19 pandemic on manufacturing firms

Survey and sample composition

The UNIDO survey on the impact of the COVID-19 pandemic on manufacturing firms (UNIDO COVID-19 survey) was collected in 26 developing and emerging industrial economies (DEIEs) between November 2020 and June 2021. The survey gathered information from about 3,900 firms in operation at the time of the data collection[16], of which more than 3,200 are in the manufacturing sector (Table A.1).

The individual firm is the unit of analysis of the survey. This has been preferred to using the "establishment" as the unit of analysis, in view of the modality in which the survey was administered—mostly online. No specific threshold in terms of number of employees was required of respondents.

The universe of reference of the survey corresponded to the population of firms operating in the manufacturing sector, defined as all activities belonging to the International Standard Industrial Classification (ISIC) Rev.4. codes 10 to 33.[17]

The survey questionnaire was distributed online, through the interface of a survey manager platform. The support of local partners such as chambers of industry and business associations provided access to firm registries and databases containing individual firm characteristics and contacts, through which firms could be contacted to participate in the survey.

[16] 4,153 firms responded to the UNIDO COVID-19 survey. Of these, 273 were not running operations at the time of the survey (and filled in a questionnaire dedicated to firms not in operation). Out of the 3,880 firms in operation, 658 were not active in manufacturing sectors (including, for instance, agriculture, mining, utilities, construction and services). The remaining 3, 222 manufacturing firms constitute the starting point of the presented analysis.

[17] The sectors falling under this definition are: food; beverages; tobacco; textiles; wearing apparel; leather; wood; paper; printing and recorded media; coke and refined petroleum; chemicals; pharmaceuticals; rubber and plastics; other non-metallic mineral products; basic metals; fabricated metal; computer, electronic and optical products; electrical equipment; machinery and equipment; motor vehicles; other transport equipment; furniture; medical and dental instruments; other manufacturing; and repair and installation of machinery and equipment.

Table A.1: Survey coverage, by country

Country	Collection period	Observations
Africa		
Congo, Democratic Republic of the	Nov 2020–Jan 2021	16
Côte d'Ivoire	Nov 2020–Jan 2021	88
Kenya	Nov 2020–Mar 2021	91
Mauritius	Dec 2020–Feb 2021	134
Rwanda	Nov 2020–Mar 2021	53
South Africa	Dec 2020–Mar 2021	74
Tunisia	Nov 2020–Mar 2021	135
Zambia	Nov 2020–Feb 2021	95
Asia		
Afghanistan	Mar–May 2021	91
Bangladesh	Mar–June 2021	108
China	Mar–May 2021	553
India	Mar–June 2021	338
Indonesia	Mar–June 2021	61
Lao, People's Democratic Republic	Feb–Apr 2021	107
Malaysia	Apr–May 2021	34
Mongolia	Feb–Apr 2021	123
Pakistan	Mar–May 2021	150
Thailand	Apr–June 2021	58
Viet Nam	Mar–May 2021	95
Latin America		
Argentina	Mar–May 2021	214
Bolivia, Plurinational State of	Mar–June 2021	109
Brazil	June–July 2021	311
Ecuador	Feb–Apr 2021	38
Mexico	May–June 2021	46
Peru	Feb–Apr 2021	49
Uruguay	Apr–May 2021	51
Total		**3,222**

Source: Authors' elaboration based on the data collected by the UNIDO COVID-19 firm-level survey.

Note: The number of observations corresponds to the number of individual firms that were in operation in manufacturing sectors at the time of the survey.

An indicator of firm-level digitalization: Production technologies (PT_i)

The UNIDO COVID-19 survey asked firms to identify the set of technologies currently used in production processes and customer relations (see Table 3 in the main text). Based on this information, a "digitalization profile" for each firm was generated by associating each firm with one technological generation as proxy for its level of digitalization.

For each of the two questions q about the set of technologies employed in production processes (q=1) and customer relations (q=2), each firm i could choose one of five options, corresponding to a specific technological generation, as follows:

$$Technological\ generation\colon\ TG_{i\ \ with\ q=1.2}^{q} = \begin{cases} \text{Analog (G 0.0)} = 1 \\ \text{Rigid (G 1.0)} = 2 \\ \text{Lean (G 2.0)} = 3 \\ \text{Integrated (G 3.0)} = 4 \\ \text{Smart (G 4.0)} = 5 \end{cases}$$

Each firm i is thus associated with two scores (TC_i^q), one for the set of technologies employed in production processes (q=1) and one for those used in customer relations (q=2).

To minimize possible biases in the responses, one control question is used for firms which self-report themselves in the highest technological category (G 4.0) in any of the two business functions: to be classified as G 4.0, in addition to selecting this generation a firm must have also invested in new software during past two years (between 2018 and the end of 2019); otherwise, it is "downgraded" to the second-highest technological generation, G 3.0.

After this adjustment, a unique "average technological generation" is calculated for each firm i, as the simple average of the two answers (TC_i^q), as follows:

$$Av.TG_i = \frac{\sum_{q=1}^{2} TC_i^q}{2}$$

Finally, based on the values of $Av.TG_i$, for each firm i we generate the categorical variable *Production technologies (PT*$_i$*)*, as follows:

$$PT_i = \begin{cases} 1\text{ (G 0.0)} \;\; \text{if } Av.TG_i = 1; Av.TG_i = 1.5 \\ 2\text{ (G 1.0)} \;\; \text{if } Av.TG_i = 2; Av.TG_i = 2.5 \\ 3\text{ (G 2.0)} \;\; \text{if } Av.TG_i = 3; Av.TG_i = 3.5\ and\ TG_i^q = 2\ for\ at\ lesat\ one\ q \\ 4\text{ (G 3.0)} \;\; \text{if } Av.TG_i = 4;\ Av.TG_i = 3.5\ and\ TG_i^q = 4\ for\ at\ lesat\ one\ q \\ 5\text{ (G 4.0)} \;\; \text{if } Av.TG_i = 5;\ Av.TG_i = 4.5 \end{cases}$$

Figure A.1 summarizes the links between the final value of PT_i assigned to a firm i and the scores of the two answer options TC_i^q provided by the same firm i. The values in the cells represent the simple average $Av.TG_i$ obtained with the corresponding values of TC_i^q, while the colour of the cells reflects the final technological generation assigned to the firm, corresponding to the final value (thus, to the category) of PT_i for the firm i.

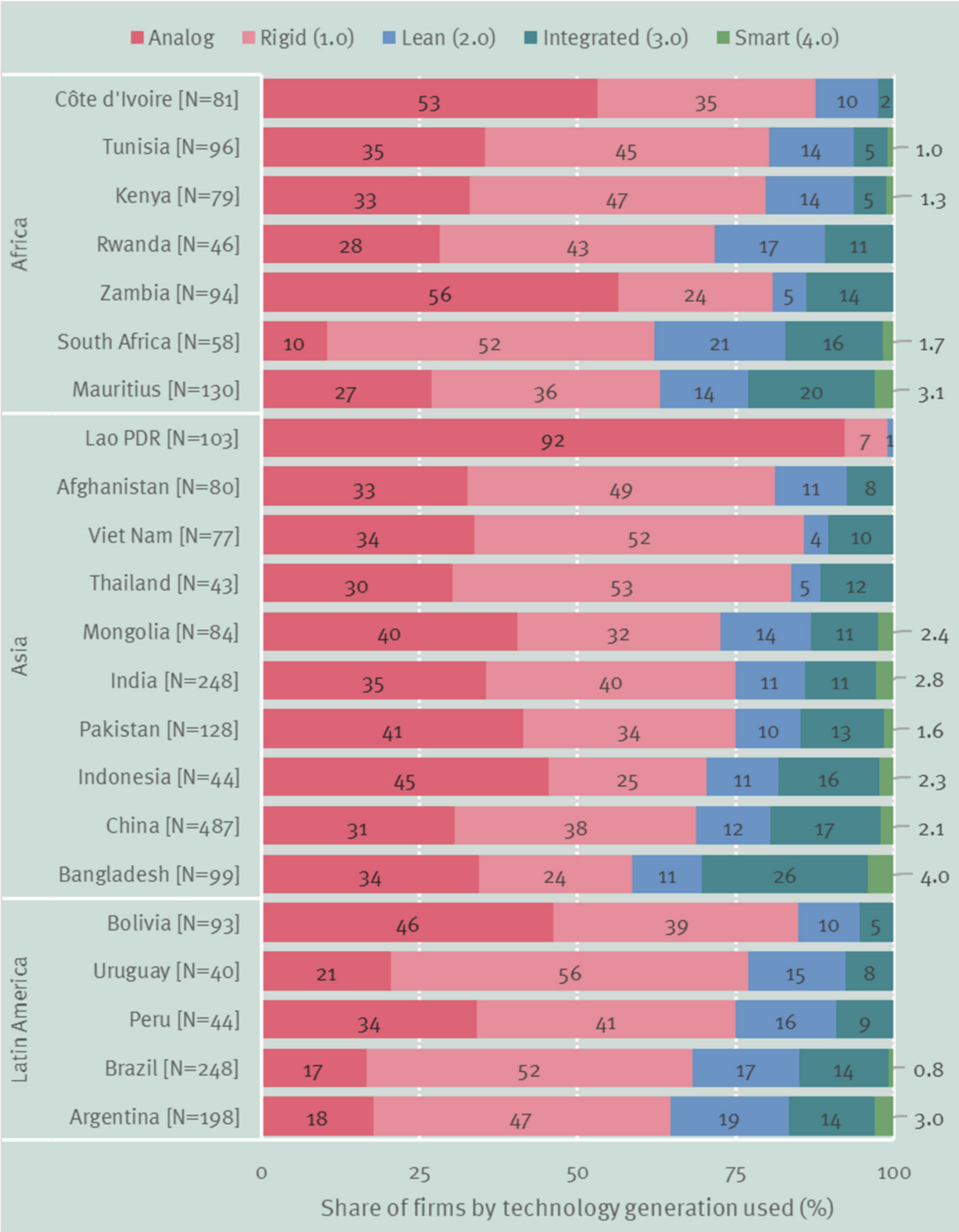
Figure A.1: Production technologies (PT$_i$): Obtaining its categories

TC_i^2 \ TC_i^1	1	2	3	4	5
1	**1**	1.5	**2**	2.5	**3**
2	1.5	**2**	2.5	**3**	3.5
3	**2**	2.5	**3**	3.5	**4**
4	2.5	**3**	3.5	**4**	4.5
5	**3**	3.5	**4**	4.5	**5**

Final value of PT_i is:	Analog (G 0.0)	Rigid (G 1.0)	Lean (G 2.0)	Integrated (G 3.0)	Smart (G 4.0)

Annex B: Additional descriptive statistics

Figure B.1: Production technologies, by country



Source: Authors' elaboration based on the data collected by the UNIDO COVID-19 firm-level survey.

Note: Sample includes individual firms that were in operation in manufacturing sectors at the time of the survey. Only countries with at least 40 valid responses to the questions on digital technologies are presented.

Table B.1: Production technologies (PT), by firm size category

Production technology (PT)	All #	All %	SMEs #	SMEs %	Large #	Large %
Analog	917	34.0%	771	41.3%	146	17.5%
Rigid (1.0)	1062	39.3%	731	39.2%	331	39.6%
Lean (2.0)	334	12.4%	179	9.6%	155	18.6%
Integrated (3.0)	345	12.8%	168	9.0%	177	21.2%
Smart (4.0)	42	1.6%	16	0.9%	26	3.1%
Obs.	2700	100.0%	1865	100.0%	835	100.0%

Source: Authors' elaboration based on the data collected by the UNIDO COVID-19 firm-level survey.

Note: SMEs = small and medium-sized firms that have up to 99 employees; *Large* = firms that have 100 or more employees. The number of employees is defined as the number of permanent employees reported by the firm at the end of 2019 minus the number of laid-off permanent workers due to the COVID-19 pandemic.

Table B.2: Summary statistics and t-test: Changes in profits and sales, by level of digitalization and firm size category

	All firms			**ADPT=0**			**ADPT=1**			**T-test n differences of averages**	
	Obs.	**Av.**	**SD**	**Obs.**	**Av.**	**SD**	**Obs.**	**Av.**	**SD**	**Diff**	**t**
SMEs											
Change in profits	1,557	-32.34	39.82	1,418	-33.36	39.47	154	-22.90	41.84	-10.46**	(-3.10)
Change in sales	1,605	-23.91	41.24	1,449	-25.10	41.10	156	-12.81	41.02	-12.29***	(-3.55)
Large											
Change in profits	731	-14.06	40.79	550	-15.16	42.11	181	-10.69	36.40	-4.473	(-1.28)
Change in sales	700	-0.71	38.60	534	-2.03	40.09	166	3.54	33.12	-5.567	(-1.62)

Source: Authors' elaboration based on the data collected by the UNIDO COVID-19 firm-level survey.

Note: SMEs = small and medium-sized firms that have up to 99 employees; *Large* = firms that have 100 or more employees. The number of employees is defined as the number of permanent employees reported by the firm at the end of 2019 minus the number of laid-off permanent workers due to the COVID-19 pandemic. ADPT = advanced digital production technologies; SD = standard deviation.

Table B.3: Summary statistics and t-test: Transformational changes, by level of digitalization and firm size category

Transformational changes	All firms			ADPT=0			ADPT=1			T-test n differences of averages	
	Obs.	Av.	SD	Obs.	Av.	SD	Obs.	Av.	SD	Diff	t
SMEs:											
Business activity online	1865	0.36	0.48	1681	0.35	0.48	184	0.48	0.50	-0.126***	(-3.38)
Organizational change	1865	0.59	0.49	1681	0.57	0.49	184	0.71	0.46	-0.132***	(-3.46)
New equipment	1865	0.17	0.37	1681	0.16	0.36	184	0.24	0.43	-0.0881**	(-3.06)
Repurposing	1865	0.20	0.40	1681	0.20	0.40	184	0.28	0.45	-0.0815**	(-2.61)
New product	1865	0.28	0.45	1681	0.27	0.44	184	0.38	0.49	-0.115***	(-3.30)
No change	1865	0.17	0.38	1681	0.18	0.39	184	0.08	0.27	0.108***	(3.68)
Large:											
Business activity online	835	0.37	0.48	632	0.34	0.47	203	0.47	0.50	-0.133***	(-3.42)
Organizational change	835	0.77	0.42	632	0.76	0.42	203	0.79	0.41	-0.0289	(-0.85)
New equipment	835	0.29	0.46	632	0.26	0.44	203	0.39	0.49	-0.131***	(-3.60)
Repurposing	835	0.25	0.43	632	0.24	0.43	203	0.29	0.45	-0.0468	(-1.34)
New product	835	0.34	0.47	632	0.32	0.47	203	0.40	0.49	-0.0778*	(-2.04)
No change	835	0.09	0.29	632	0.10	0.30	203	0.07	0.26	0.0226	(0.97)

Source: Authors' elaboration based on the data collected by the UNIDO COVID-19 firm-level survey.

Note: SMEs = small and medium-sized firms that have up to 99 employees; *Large* = firms that have 100 or more employees. The number of employees is defined as the number of permanent employees reported by the firm at the end of 2019 minus the number of laid-off permanent workers due to the COVID-19 pandemic. ADPT = advanced digital production technologies; SD = standard deviation.

Table B.4: Firm characteristics: Main summary statistics, by region

Variable	Obs.	Av.	SD	Min	Max	Obs.	Av.	SD	Min	Max	Obs.	Av.	SD	Min	Max
	Africa					Asia					Latin America				
Production technology:															
Analog	602	0.36	0.48	0	1	1,413	0.38	0.49	0	1	685	0.23	0.42	0	1
Rigid	602	0.39	0.49	0	1	1,413	0.36	0.48	0	1	685	0.47	0.50	0	1
Lean	602	0.13	0.34	0	1	1,413	0.10	0.30	0	1	685	0.16	0.37	0	1
ADPT	602	0.12	0.33	0	1	1,413	0.16	0.37	0	1	685	0.13	0.34	0	1
Impact of COVID-19 pandemic:															
Change in profits	481	-35.21	35.97	-100	100	1,209	-22.44	41.68	-100	100	613	-27.81	42.30	-100	100
Change in sales	510	-31.06	33.32	-100	100	1,268	-14.63	43.23	-100	100	527	-8.50	42.57	-100	157
Transformational changes:															
Business activity online	602	0.45	0.50	0	1	1,413	0.38	0.48	0	1	685	0.28	0.45	0	1
Organizational change	602	0.65	0.48	0	1	1,413	0.57	0.49	0	1	685	0.79	0.41	0	1
New equipment	602	0.15	0.36	0	1	1,413	0.26	0.44	0	1	685	0.14	0.35	0	1
Repurposing	602	0.27	0.45	0	1	1,413	0.22	0.41	0	1	685	0.17	0.38	0	1
New product	602	0.29	0.46	0	1	1,413	0.30	0.46	0	1	685	0.29	0.45	0	1
No change	602	0.11	0.32	0	1	1,413	0.19	0.39	0	1	685	0.10	0.30	0	1
Employment:															
Total employment	602	250.66	125	1	21,800	1,413	398.07	2721.4	1	73,200	685	205.63	701.98	1	10,217
Total employment (log)	602	4.17	1.41	0	9.99	1,413	4.22	1.69	0	11.20	685	3.87	1.57	0	9.23
Total employment (log), squared	602	19.34	13.08	0	99.79	1,413	20.63	15.76	0	125.46	685	17.44	13.70	0	85.23
Innovation:															
Process innovation	602	0.36	0.48	0	1	1,413	0.40	0.49	0	1	685	0.35	0.48	0	1
Product innovation	602	0.48	0.50	0	1	1,413	0.57	0.50	0	1	685	0.54	0.50	0	1
Organizational innovation	602	0.30	0.46	0	1	1,413	0.25	0.43	0	1	685	0.32	0.47	0	1
Investment in new software	602	0.27	0.45	0	1	1,413	0.23	0.42	0	1	685	0.36	0.48	0	1
GVC	602	0.21	0.41	0	1	1,413	0.27	0.44	0	1	509	0.33	0.47	0	1
Export	601	0.28	0.45	0	1	1,413	0.27	0.45	0	1	684	0.12	0.33	0	1
Ownership:															
Private firm (non-foreign invested)	602	0.65	0.48	0	1	1,413	0.83	0.38	0	1	684	0.84	0.36	0	1
Foreign invested	602	0.33	0.47	0	1	1,413	0.12	0.32	0	1	684	0.13	0.33	0	1
State-owned and other	602	0.02	0.13	0	1	1,413	0.05	0.23	0	1	684	0.03	0.17	0	1

Source: Authors' elaboration based on the data collected by the UNIDO COVID-19 firm-level survey.

Note: ADPT = advanced digital production technologies; GVC = global value chain; SD = standard deviation.

Annex C: Additional results

Table C.1: Drivers of advanced digital technologies (ADP): Probit coefficients

Dependent variable: ADPT	(1)	(2)
Process innovation	0.258***	0.251***
	(0.068)	(0.071)
Product innovation	0.126*	0.143**
	(0.069)	(0.072)
Organizational innovation	0.059	0.011
	(0.075)	(0.079)
Total employment (log)	0.135***	0.117***
	(0.024)	(0.026)
Ownership: foreign invested	0.294***	0.278***
	(0.089)	(0.094)
Ownership: state-owned and other	0.256*	0.240
	(0.152)	(0.156)
Investment in new software	0.288***	0.270***
	(0.073)	(0.077)
GVC		0.188**
		(0.079)
Export		0.119
		(0.084)
Constant	-2.274***	-2.136***
	(0.247)	(0.255)
Sector	Yes	Yes
Country	Yes	Yes
Obs.	2,699	2,514

Source: Authors' elaboration based on the data collected by the UNIDO COVID-19 firm-level survey.

Note: The base category for ownership is *Private firm (non-foreign invested)*. Standard errors in parentheses: *p<0.10; **p<0.05; ***p<0.01. ADPT = advanced digital production technologies; GVC = global value chain.

Table C.2: Drivers of transformational change: Probit coefficients

Dependent variable:	Business activity online	Organizational change	New equipment	Repurposing	New product
	(1)	(2)	(3)	(4)	(5)
ADPT	**0.293*** **	**0.181** **	**0.274*** **	**0.163* **	**0.225*** **
	(0.081)	**(0.086)**	**(0.084)**	**(0.083)**	**(0.082)**
Total employment (log)	-0.036*	0.148***	0.078***	0.052**	-0.011
	(0.020)	(0.021)	(0.022)	(0.021)	(0.021)
Process innovation	0.178***	0.249***	0.231***	0.217***	0.600***
	(0.060)	(0.059)	(0.066)	(0.064)	(0.061)
Product innovation	0.448***	0.160***	0.323***	0.259***	0.344***
	(0.060)	(0.060)	(0.064)	(0.063)	(0.060)
Organizational innovation	0.236***	0.327***	0.113	0.258***	0.145**
	(0.066)	(0.067)	(0.070)	(0.067)	(0.065)
Investment in new software	0.142**	0.209***	0.236***	-0.050	0.117*
	(0.068)	(0.069)	(0.071)	(0.071)	(0.067)
GVC	0.040	0.112	0.097	0.029	-0.019
	(0.067)	(0.069)	(0.072)	(0.071)	(0.068)
Export	-0.051	-0.044	0.201***	-0.011	0.037
	(0.070)	(0.071)	(0.077)	(0.074)	(0.072)
Ownership: foreign-invested	-0.114	-0.014	-0.064	-0.195**	-0.230***
	(0.083)	(0.084)	(0.090)	(0.087)	(0.087)
Ownership: state-owned and other	0.071	-0.156	-0.156	-0.111	-0.110
	(0.135)	(0.140)	(0.154)	(0.150)	(0.141)
Constant	-0.580***	-1.502***	-1.337***	-0.899***	-1.361***
	(0.187)	(0.191)	(0.192)	(0.187)	(0.197)
Sector	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes
Obs.	2,514	2,514	2,503	2,514	2,514
Degrees of freedom	55	55	54	55	55

Source: Authors' elaboration based on the data collected by the UNIDO COVID-19 firm-level survey.

Note: The base category for ownership is *Private firm (non-foreign invested)*. Standard errors in parentheses: *p<0.10; **p<0.05; ***p<0.01. ADPT = advanced digital production technologies; GVC = global value chain.

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