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DOES VALUE CHAIN PARTICIPATION FACILITATE THE ADOPTION OF DIGITAL TECHNOLOGIES IN DEVELOPING COUNTRIES?

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Does value chain participation facilitate the adoption of digital technologies in developing countries?

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Table of Contents

1. Introduction 1
2. Literature review 3
   2.1 Digital technologies: characteristics, impacts and adoption strategies 3
   2.2 Firm capabilities and technology adoption 5
   2.3 Value chain participation and technology adoption 6
3. Conceptual framework 8
4. Methodology 9
   4.1 The data 9
   4.2 Empirical approach and variables 10
5. Results and discussion 12
   5.1 Technology adoption: some descriptive evidence 12
   5.2 Characterizing technology adoption patterns 14
   5.3 From adoption to firm performance 22
6. Concluding remarks 25
References 27
Appendix 31

List of Figures

Figure 1: Conceptual framework 8
Figure 2: Technology adoption across countries and size groups 13
Figure 3: Digital readiness across countries and size groups 14
Figure 4: Average marginal effects on the likelihood of falling into the highest group by technological generation 20
Figure 5: Average marginal effects on the likelihood of belonging to the group of moving forward firms 22
Figure 6: Relative productivity of ADP technology adopters and non-adopters, by size and industry 23
Figure 7: Enablers of productivity in manufacturing firms 25

List of Tables

Table 1: Determinants of ADP technology adoption: probit estimations 15

Table 2: Determinants of advanced manufacturing technology adoption across business functions: multivariate probit estimations 17

Table 3: Technological generations and their determinants: ordered probit estimations 19

Table 4: Determinants of digital readiness: ordered probit estimations 21

Table 5: Technology adoption, value chain participation and labour productivity: OLS and 2SLS estimations 24

Abstract

The adoption of technologies from abroad is an important driver of firm performance and industrial catching up in developing economies. Recent research finds digital technologies to be at the core of a new wave of technological change—the Fourth Industrial Revolution. This paper seeks to understand whether value chain participation facilitates the adoption of new digital technologies by manufacturing firms in developing economies. To understand the drivers of digital technology adoption, we focus on the interrelationships between firms' international activities and their internal resources and capabilities. We employ firm-level data collected through a recent UNIDO survey of manufacturing firms in Ghana, Thailand and Viet Nam. Our findings suggest that while the adoption of digital technologies remains limited in the three countries under consideration, firms' participation in a value chain and their investments in building up internal technological capabilities, are important drivers of technology adoption.

Keywords: GVCs; technology adoption; technological capabilities; innovation

JEL codes: O12, O13, O33

1. Introduction

The diffusion of digital manufacturing technologies is increasingly attracting the attention of academics and policymakers. According to observers, digital technologies, including artificial intelligence, cloud computing, big data analytics and advanced robotics, are all likely to play an increasingly important role in production and innovation processes in the near future (Sturgeon, 2017). Part and parcel of the information and communication technology (ICT) revolution which precedes it, the digitalization of manufacturing lies at the core of the new wave of technological change, with sweeping implications for economies and societies, giving rise to various expressions such as the Fourth Industrial Revolution and Industry 4.0 (Schwab et al., 2018).

The digitalization of manufacturing is widely expected to contribute to productivity and economic growth across firms, industries and countries (Schwab et al., 2018). Yet, the debate about the potentially adverse impacts of digital technologies on the industrial development of developing and emerging industrial countries continues. Specifically, digitalization may reduce the role labour costs play in the location decisions of MNCs and at the same time, increase that of ICT skills and infrastructure (Hallward-Driemeier and Nayyar, 2017; Rehnberg and Ponte, 2018). These trends may contribute to "raising the bar" in terms of the requirements for developing countries to industrialize and integrate in global production.

This paper contributes to these debates by exploring firm-level determinants for the adoption of advanced digital production (ADP) technologies in developing and emerging industrial economies.[1] We study technology adoption by building on economics literature on the diffusion of new technologies at the firm level. The key factors, according to the literature, that shape the incentives and constraints that drive the adoption (or lack thereof) of new technologies at firm level are firms' internal resources, knowledge base and technological capabilities (Bell and Pavitt, 1993; Pietrobelli, 1997; Battisti et al., 2009; Grazzi and Jung, 2019). We extend this line of research by considering additional determinants of technology adoption, namely the extent of firms' international activities, particularly their participation in global value chains (GVCs), as exposure to international trade and production networks is increasingly being associated with a wider diffusion of knowledge across countries and greater opportunities for learning and capability development (Morrison et al., 2008; Saliola and Zanfei, 2009).

[1] We define ADP technologies as any technology being used in manufacturing firms that belongs either to the generation of Industry 4.0 technologies or to the previous generation of advanced ICTs. See Table A2 in the Appendix for an overview of the types of manufacturing technologies that belong to these two generations in accordance with the UNIDO Survey "Adoption of digital technologies by industrial firms".

Building upon these strands of literature, we introduce a conceptual framework to identify the determinants of digital technology adoption by manufacturing firms in developing and emerging industrial economies. We understand a firm's adoption strategy to be a gradual process that is influenced by both internal and external factors to the firm. A firm that adopts new technologies is driven as much by its own internal capabilities and knowledge base as it is by incentives and pressures deriving from its exposure to, and interaction with, international trade and production networks.

The degree of digital technology diffusion within the innovation strategies of firms in developing and emerging industrial economies experiencing rapid growth has become increasingly important in recent years. Thus, we test our framework against data collected through UNIDO's survey on manufacturing firms' adoption of digital technologies in three countries—Ghana, Thailand and Viet Nam. The survey covers manufacturing firms across size, sectors and geographical location. These three countries are interesting in terms of the contribution of foreign sources of knowledge to domestic technological change, as they are all gradually integrating within GVCs (Amendolagine et al., 2017; UNIDO, 2018).

We take advantage of the granularity of the UNIDO survey by studying both the incidence and the intensity of digital technology adoption by the firms in our sample, both at the individual firm level and across different business operations. Our findings suggest that manufacturing firms in the three countries have yet to undergo a significant process of digitalization. Differences between the countries do, however, exist. Firms that adopt ADP technologies are typically larger and have a higher proportion of skilled workers. Digital technology adoption is also related to firm's investments in activities that support the development of their internal capabilities, such as R&D, training and investment in new equipment. Firms that adopt digital technologies are also far more likely to be integrated within value chains relative to firms that do not adopt such technologies.

Building on information on firms' current adoption strategies and their formal plans and actions associated with digitalization, we also consider the extent of firms' readiness to tackle technological change. We find that the determinants explaining firms' current adoption patterns also contribute to explaining their degree of readiness. Finally, we are also interested in the relationship between technology adoption and firm performance, particularly with regard to labour productivity. Our findings point to the existence of a productivity premium associated with the adoption of new technology. However, it must be emphasized that survey data consists of a single cross-section, making it impossible to test causal claims. Our aim is rather to identify firm-level characteristics that may be associated with the adoption of digital technologies in a developing country context.

The paper is structured as follows. Section 2 presents a review of the literature on technology adoption, firm-level technological capabilities and value chain participation. Bringing together these distinct strands of literature, section 3 puts forward a conceptual framework to explore different hypotheses on the determinants and obstacles to the adoption of digital technologies in developing countries. Section 4 describes the data and our empirical approach. Section 5 discusses the results of the empirical exercise and section 6 concludes.

2. Literature review

This paper builds on three strands of literature that are relevant for understanding the relationships between the adoption of digital technologies, firm-level capabilities and value chain participation. The first strand is the literature on the determinants of the adoption of new technologies—such as Industry 4.0 technologies and ICTs—and their impact on firm performance. The second strand of literature this paper builds on is the role of technological capabilities at firm level. Third, our study draws on the literature investigating the link between value chain participation, learning and productivity in developing country firms.

2.1 Digital technologies: characteristics, impacts and adoption strategies

The "Fourth Industrial Revolution" concept is based on the growing convergence and complementarity between different emerging technology domains ranging from information and communication technologies (ICTs) to digital technologies and new materials (Schwab et al., 2018). While there are several competing classifications of Industry 4.0 technologies, various observers agree on the relevance of artificial intelligence, big data analytics, cloud computing and the Internet of Things (IoT) (Sturgeon, 2017). These technologies function as enablers of a vast array of manufacturing applications, ranging from advanced enterprise resource planning systems (ERPs) and manufacturing execution systems (MESs) to additive manufacturing (or 3D printing).

The digital technologies associated with Industry 4.0, in turn, have been enabled by advances made in ICTs, which have been ongoing for the past three decades. From this perspective, the Fourth Industrial Revolution can be understood as arising from the ICT revolution. Technical progress in ICTs since the 1980s, including the rise of mass market personal computers, the spread of connectivity infrastructure, the growing use of digital design tools in manufacturing and services, and the increase in the inter-operability of different information technology systems, all contribute to explaining the rise in the current wave of digitalization (Sturgeon, 2017).

As research into the diffusion and impact of new digital technologies at firm level remains limited, some insights can be derived from the literature on the determinants of ICT adoption.[2] This line of research suggests that adopting ICTs enables faster communication and information processing, thereby decreasing internal coordination costs, facilitating firms' decision-making processes, and reducing the potential for market failures deriving from information asymmetries (Cardona et al., 2013). ICTs may also foster firm restructuring, making internal processes more flexible (Grazzi and Jung, 2019). Moreover, ICTs could provide the foundation upon which businesses innovate, acting as general purpose technologies (GPTs) (Bresnahan and Trajtenberg, 1995).

Empirical work at the firm level confirms these findings. Studies of ICT adoption in both industrialized, developing and emerging industrial economies point to a positive productivity effect of new technologies (see, for instance, Arvanitis and Loukis, 2009; Aboal and Tacsir, 2018; Grazzi and Jung, 2019). While evidence on the impact of digital technology adoption remains unexplored, a recent study on the use of big data analytics by German firms suggests that new practices in analysing data enhance firms' decision-making possibilities, thus supporting innovativeness (Niebel et al., 2019). Big data analytics is found to be an important determinant in the likelihood of firms commercializing new product innovations.

This literature, however, also identifies significant heterogeneity in the incidence and intensity of adoption of new technologies across firms. Estimates of adoption rates for digital technologies are scarce. Available estimates from OECD countries suggest that the diffusion of digital applications lags behind, with average adoption rates ranging from under 50 per cent for the use of social media to approximately 12 per cent for big data analytics (Andrews et al., 2018). While comprehensive estimates for developing and emerging industrial economies are unavailable, one would expect to find an even more uneven adoption landscape.

The heterogeneity we observe in adoption rates raises questions about the possible determinants and obstacles firms encounter when new productivity-enhancing technologies appear on the market. Literature on technology adoption investigates both inter- and intra-firm factors. Early adoption research points to the role of information on the availability of new technologies. Epidemic models, for instance, predict that the diffusion of new technologies across firms increases over the course of time as adoption costs and risks decline based on learning effects (see, for instance, Mansfield, 1963). Early adopters disseminate information on new technologies,

[2] It is worth noting that a large body of literature exists on the link between ICT diffusion and productivity growth at the aggregate level (see, for instance, Jorgenson, 2001; David and Wright, 2005).

leading other firms to adopt them and disclose further information, until eventually a saturation point is reached (Hall and Khan, 2003).

The persistence of differences between different firms led to the development of models with a larger emphasis on the interlinkages between different firm characteristics, differentials in the expected returns from the adoption of new technologies, and adoption strategies (Karshenas and Stoneman, 1993). "Rank" models are premised on the view that firms will adopt new technologies up to the point where the marginal expected gross profit gain from their use equals the marginal expected cost, taking into account firms' internal characteristics alongside the specific features of the industries and local markets within which the firms are active, as well as inter-firm epidemic effects (Karshenas and Stoneman, 1993; Battisti et al., 2009).

Recent research on the intra-firm determinants of adoption extends this framework by focussing on the complementarity of the introduction of new technologies with a firm's organizational design and knowledge base—its "intangible" assets. Building on Milgrom and Roberts' (1995) work, this line of research views the decision to adopt new technologies, such as ICTs and digital applications, as being determined by the firm having access—within its own boundaries—to key assets such as other enabling technologies, workers' skills and managerial practices. The presence of these intangibles ensures that new technologies are successfully implemented, and that returns from their adoption are fully appropriated (Gómez and Vargas, 2012; Gallego et al., 2015).

2.2 Firm capabilities and technology adoption

Literature on the role of intangible assets is related to research on firm-level technological capabilities. Originating at the intersection between development and evolutionary economics, the literature on capabilities explores firms' investments into their own capabilities to generate and manage technological change. In this framework, technological capabilities can be understood as the combination of knowledge and skills—of a technological, managerial or organizational nature—that are required for firms to identify, operate and improve the technologies they use (Lall, 1992; Pietrobelli, 1997). As is the case for other intangible assets, technological capabilities are idiosyncratic and deeply embedded within organizations. They originate from the accumulation of both skills and production experience over time (Morrison et al., 2008).

Capabilities are heterogeneous and are related, in the literature, with activities ranging from investment to production and relationship-building (Lall, 1992). The accumulation of technological and production capabilities is understood as a continuous process characterized by cumulativeness and path-dependency. In this view, firms continuously adapt to technological change in the wider economy by investing in their own knowledge bases—for instance, by investing in in-house R&D activities, or by training human capital through formal education, on the job training and general production experience—while also absorbing external knowledge through FDI, value chain participation or capital goods imports (Bell and Pavitt, 1993).

The literature suggests several ways in which technological capabilities may interact with the technology adoption process. One is related to the concept of absorptive capacity. Only firms with sufficiently developed technological capabilities recognize value in new sources of external information, and consequently endeavour to assimilate and apply them to new commercial ends (Cohen and Levinthal, 1990). Another interrelated argument focuses on learning. An emphasis on capabilities implies that technology can hardly be transferred to a firm like a physical product, nor can it be bought off the shelf (Lall, 1992). Rather, its effective implementation is likely to require a process of active capability building in the absence of which efficiency gains will not necessarily materialize (Bell and Pavitt, 1993).

2.3 Value chain participation and technology adoption

Finally, this paper is connected to the literature on GVC participation and firm-level learning. GVCs represent a form of industrial organization wherein the geographical fragmentation of production is accompanied by its functional integration across borders, leading to a cross-country pattern of specialization (and trade) in tasks rather than in products.[3] Participation in international trade and production networks is considered a viable channel for knowledge transfer from multinational corporations to suppliers further upstream or downstream in the chain (World Bank, 2017).

Interest in the interplay between value chain participation and technology adoption stems from research on the sources of technological change, which stresses the role of knowledge absorption from abroad for productivity growth in domestic economies, and from literature on knowledge spillovers from FDI (see, respectively, Keller, 2004; and Javorcik, 2004). For manufacturing firms in developing and emerging industrial economies, learning about new digital technologies—the development of which remains concentrated in a small number of firms in industrialized

[3] The World Bank (2020) estimates that as of 2015, GVCs represented about 50 per cent of global trade.

economies—may depend on their degree of integration in international trade and production networks (Zanello et al., 2016).

The literature on GVCs points to different hypotheses on the role of value chain participation in technology adoption. International business scholars, for instance, have explored the extent to which firms learn by supplying MNCs and their subsidiaries. Research into patterns of supplier development through knowledge-sharing linkages between customers and suppliers has been carried out in the mobile telecommunications and automobile industries, among others (Sako, 2004; Alcacer and Oxley, 2014). This literature is particularly notable for its emphasis on the relational aspects of value chain participation. Supplying certainly contributes to learning, but so does *whom* one supplies to (Alcacer and Oxley, 2014).

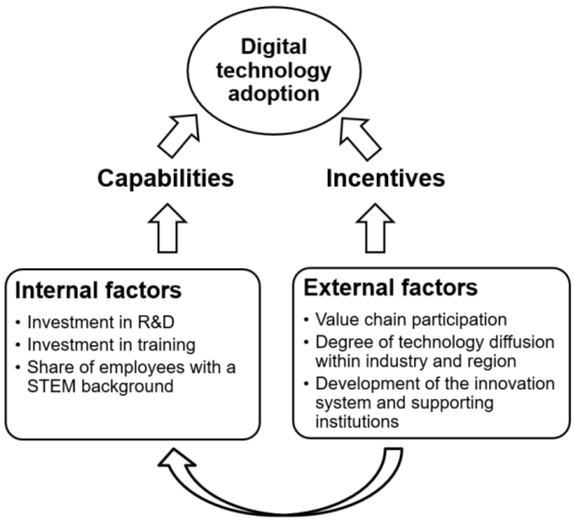
That the modality of a firm's involvement in value chains should affect the extent of knowledge transfer more than mere participation is also a central tenet in the international development literature on GVCs. This literature suggests that whether a transfer of knowledge from MNCs to their suppliers occurs as part of a voluntary effort, or rather arises involuntarily, depends on the type of relationship lead firms and their suppliers are embedded in –i.e. the "governance" of value chains (Pietrobelli and Saliola, 2008). As lead firms engage in the coordination of their partners' activities upstream and downstream, they opt for different forms of value chain governance. Different modes of governance, in turn, give rise to different incentives for lead firms to engage in knowledge transfer and learning promotion (Gereffi et al., 2005).

In instances where value chain transactions require the exchange of relatively complex information and MNCs have an interest in increasing the production efficiency of suppliers located upstream, for instance, lead firms may directly engage in knowledge transfer activities (Saliola and Zanfei, 2009). Mechanisms include face-to-face interactions, the training of workers and managers by lead firms, or technology licensing (De Marchi et al., 2018). In other instances, suppliers may learn indirectly, for instance, through the reception of detailed product specifications and feedback on product performance (Perez-Aleman, 2010). This form of support is often chosen by lead firms that want to ensure compliance and to consistently bring suppliers up to a certain level of production quality – but not beyond simple manufacturing tasks (De Marchi et al., 2018).

3. Conceptual framework

A firm will decide to take up a new technology when the expected gains resulting from adopting that new technology—in terms of, for instance, an increase in market share, a reduction in processing costs, or the possibility to increase selling prices—exceed its costs (Karshenas and Stoneman, 1995; Battisti et al., 2009). As the strands of literature we have reviewed so far suggest, however, this decision is further shaped by the interplay of internal and external factors. External factors influence a firm's adoption strategy by determining the incentives to search for knowledge external to the firm or, alternatively, the pressures that induce the firm to adopt new technologies. Intra-firm factors, in turn, shape firms' capacity to respond to the challenges of technological change: whether firms can identify and successfully integrate new technologies in their operations hinges on the extent of their capabilities (Cohen and Levinthal, 1990) (see Figure 1).

Figure 1: Conceptual framework



Source: Authors' elaboration.

A firm's exposure to international trade and production networks can act as an inducement to adopt digital technologies, and the relationship with foreign (lead) firms may itself promote the development of capabilities. Several mechanisms are at play. Firms with foreign ownership and subsidiaries of foreign firms and MNCs, for instance, may have easier access to new technologies developed abroad compared with purely domestic firms. Exporters and two-way traders are exposed to international competition and may opt to digitalize earlier relative to firms that cater to domestic consumers in order to gain a competitive edge. In some instances, the very possibility of gaining entry to GVCs for suppliers in developing and emerging industrial economies hinges on having access to advanced ICTs and digital technologies. Similarly, suppliers may be pressured by their international customers to digitalize part of their operations (De Marchi et al., 2018), highlighting a two-way causality linking digital adoption to GVC integration.

Among the relevant factors external to the firm, we also consider the degree of technology diffusion in the relevant sector and geographical area to reflect epidemic learning effects (Mansfield, 1963; Hall and Khan, 2003). Because each firm can learn about a new technology from its peers and competitors within the same sector and in neighbouring areas, as the costs associated with gathering information about the technology decrease over time, more and more firms may choose to adopt the technology during any period, leading to an increasing rate of adoption. The characteristics of the industry in which a firm operates is also likely to shape digital adoption decisions. Different sectors engender different incentives and technological opportunities (Klevorick et al., 1995). Finally, the innovation system in which a firm is embedded is also an additional determinant of digital technology adoption (Pietrobelli and Rabellotti, 2011).

External incentives, however, are moderated by each firm's set of resources, knowledge base and technological capabilities. Internal incentives such as investment in R&D and training activities contribute to the enhancement of the firm's knowledge base, increasing its capability to identify, absorb and smoothly adapt new technologies within its operations (Bell and Pavitt, 1993). Similarly, having access to a skilled labour force is an important determinant of technology adoption. An educated and skilled workforce is better able to identify new technologies that could be employed to raise a firm's efficiency and better placed to install and maintain them over time. Internal factors may also indirectly affect adoption by influencing the productivity returns of investments in new digital technologies, which feed back into the original adoption decision (Andrews et al., 2018).

4. Methodology

4.1 The data

Data for this study is drawn from the UNIDO Survey "Adoption of Digital Technologies by Industrial Firms" carried out in Ghana, Thailand and Viet Nam in 2019. The survey covered manufacturing firms in six industries: food products, beverages and tobacco; textiles, textile products, leather and footwear; wood and furniture; plastic and rubber; metal products; computer, electronics and optical products; and automotive and auto parts.[4]

[4] Respectively ISIC Rev. 4 codes 1010 to 1200, 1311 to 1520, 1610 to 1629 and 3100, 2210 to 2220, 2410 to 2599, 2610 to 2670, and 2910 to 3091. Sectoral coverage is not homogenous across the three countries. In Ghana, firms were surveyed in the food and beverages, textile, wood and furniture, plastics and metal products industries. In the other two countries, firms were surveyed in the food and beverages, textile, computer and electronics and automotive industries.

The survey investigated the current and predicted patterns of technology adoption of firms in the three countries. The survey followed the approach put forward in IEL (2018) and focussed on a range of technologies listed by level of sophistication, from simple, manual techniques up to state-of-the art digital technologies and applications, allowing to derive a very granular understanding of technology adoption patterns in the three countries. Moreover, technologies were grouped according to the business functions they refer to.[5] For our analysis, we group technologies into four "generations" in ascending order, where the third and fourth group, respectively, indicate advanced ICTs and digital technologies associated with the Industry 4.0 concept.[6] These two generations are taken together as a proxy for ADP technologies.

4.2 Empirical approach and variables

Our approach to study the adoption of ADP technologies—that is, technologies belonging to the group of advanced ICTs and Industry 4.0 technologies—is two-fold. First, we are interested in identifying the main determinants of technology adoption for manufacturing firms in Ghana, Viet Nam and Thailand in order to provide a characterization of adoption patterns in the three countries. For this part of the analysis, we focus on inter- and intra-firm adoption, and we distinguish between firms' current adoption patterns and their readiness to face digitalization.[7] Secondly, we consider the relationship between ADP technology adoption and firm performance with a focus on labour productivity.

Building on our conceptual framework and on previous empirical work on the determinants of technology adoption (see, for instance, Baldwin, 1995; Fabiani et al., 2005; Battisti et al., 2009; Gómez and Vargas, 2012; Grazzi and Jung, 2019), we start by modelling the likelihood of firms to adopt ADP technologies as a function of firm-level characteristics and environmental factors. In line with previous literature, we employ different probability models to test the likelihood of digital technology adoption conditional on 'rank' effects, i.e. firms' structural characteristics, resources, proxies for technological capabilities, and exposure to international trade and production networks (Karshenas and Stoneman, 1993). We also consider "epidemic" effects, under the assumption that firms gain knowledge of new technologies by learning from their peers

For more information about the sample composition and sampling strategy of the UNIDO survey, see Kupfer et al. (2019).

[5] See Appendix, Table A2, for an overview of the technologies and business functions covered by the survey.

[6] See Kupfer et al. (2019) for a detailed discussion of the definition of technological generations.

[7] We use the readiness index developed in Kupfer et al. (2019). The index combines the current and expected adoption of digital technologies reported by firms with plans and actions already in place to reach the projected digital generation. This is done in such a way that the expectations about future technology generation are "grounded" on the likelihood of the firm actually reaching that level.

and competitors within the same geographic location and industry (Karshenas and Stoneman, 1993; Grazzi and Jung, 2019). Finally, we control for country- and sector-specific effects.

Our basic estimating equation is as follows, where subscript *i* indicates the firm:

$$\Pr(Digital\ Technology\ Adoption_i = 1) = \beta_0 + \beta_1\ Rank\ effects_i + \beta_2\ Epidemic\ effects_i + \beta_3 Country\ effects_i + \beta_4\ Sector\ effects_i + \varepsilon_i \quad (1)$$

Our 'rank' effects include a set of structural characteristics that are typically included in the literature on technology adoption. These include firm size, age and ownership. The motivation for considering these variables stems from the observation that larger firms have fewer financial constraints and may thus be in a better position to withstand the costs associated with new technologies (Fabiani et al., 2005). Similarly, foreign-owned firms have been found to be early adopters of new technologies (Gómez and Vargas, 2012). With regard to firm age, the existing literature has yet to reach consensus. While older firms may be considered more prone to adopting new technologies in light of their accumulated technology experience, they may also face higher switching costs and suffer from organizational inertia (Coad et al., 2016).

In light of the conceptual framework outlined above, we are particularly interested in the relative roles of firms' investments in their own technological capabilities—including investments in R&D and training activities and the availability of a skilled labour force—and the extent of their participation in value chains (Morrison et al., 2008). Firms endowed with greater capabilities and higher levels of human capital are, in principle, better equipped to identify and successfully implement new technologies available on the market (Pietrobelli, 1997). Similarly, firms that are exposed to international trade and production may be more prone to taking up new technologies (Saliola and Zanfei, 2009). In line with previous literature, we model epidemic learning effects as the share of other firms that have adopted a technology in the same region and sector (Hollenstein, 2004; Gallego et al., 2015).

Finally, characteristics related to the countries and sectors firms operate in are also typically included in such analyses. They are likely to influence the decision to adopt new technologies by specifying, respectively, local market conditions and the industry-specific technological opportunities that firms face at any point in time (Klevorick et al., 1995). Table A1 in the Appendix provides a more detailed overview of variables used in our empirical analysis, including their definitions and summary statistics.

In the second part of the analysis, we study whether firms' adoption of ADP technologies is associated with higher firm performance. For this part, we focus on the relationship between technology adoption and productivity. To do so, we estimate the following equation with subscripts i, j, and h indicating firm, country and industry, respectively:

$$y_{ijh} = \beta_0 + \beta_{jh} + \beta_1 ADOPTION_{ijh} + \beta_2 X_{ijh} + \varepsilon_{ijh} \quad (2)$$

where *y* denotes labour productivity measured as sales per employee, technology adoption takes the form of either a binary or a categorical variable indicating whether and to what extent the firm has adopted advanced manufacturing technologies, and *X* is a vector of firm characteristics, including their structural characteristics—such as size, age, ownership patterns, availability of a high-quality fixed broadband connection—their human capital endowments, and two dummies capturing whether they take part in a value chain and whether they invest in their own technological capabilities. These are proxied by looking at firms' investments in R&D, training and new equipment.

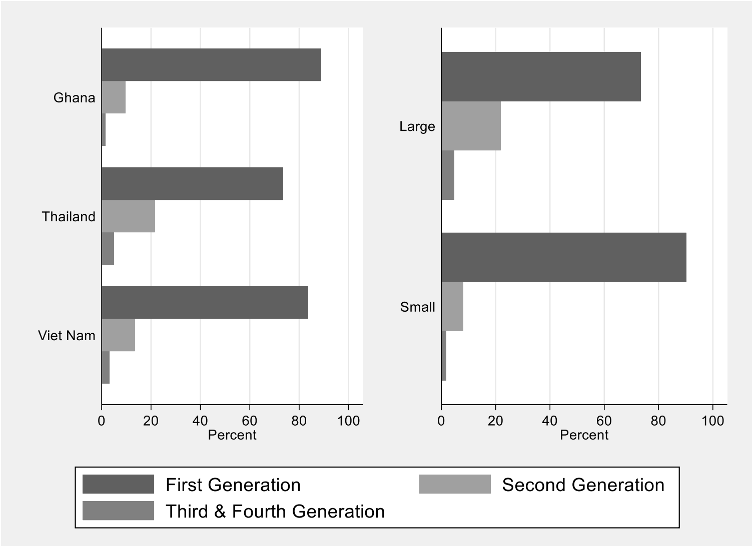
5. Results and discussion

5.1 Technology adoption: some descriptive evidence

The UNIDO survey provides detailed information on firms' use of technologies belonging to different generations—from analogic and manual tools to ICTs to increasingly sophisticated technologies associated with the Fourth Industrial Revolution—for each of the business functions they perform (Table A2). To gauge the extent of digital adoption across firms and business functions, we follow the approach proposed by Kupfer et al. (2019) and use two aggregate indicators to proxy for a firm's current digital adoption rate (*DAR_C*) and its 'digital readiness' index (*DRI*). We then group firms into categories based on their aggregate adoption status.

We find that the adoption of ADP technology, that is, technologies belonging to the third and fourth generations, remains limited in our sample. Only approximately 3.2 per cent of surveyed manufacturing firms currently employ technologies belonging to either of the two highest technological generations. Figure 2 below illustrates adoption patterns across countries and size groups. While adoption patterns do not differ markedly across the three countries, Ghana appears to have fewer firms that belong to a higher technological generation relative to Thailand and Viet Nam. With regard to firm size, on the other hand, there appears to be a somewhat positive relationship between digital adoption and firm size.

Figure 2: Technology adoption across countries and size groups

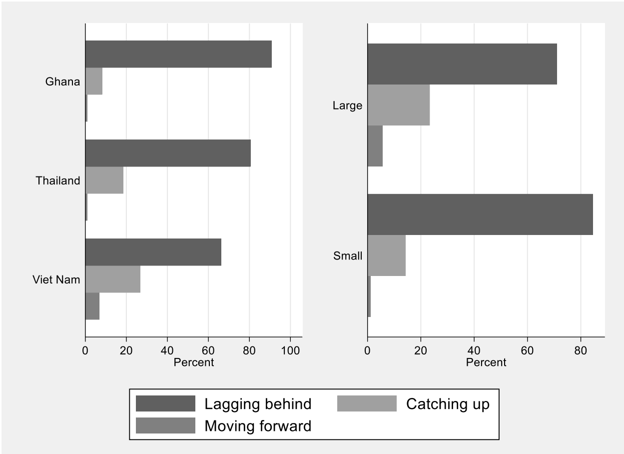


Source: Authors' elaboration based on the UNIDO survey "Adoption of Digital Technologies by Industrial Firms."

Since the UNIDO survey not only provides information on firms' current adoption rates, but also on their expectations for future technology generation and their ongoing plans and actions to keep up with technological change, we can also look at firms' digital readiness index (*DRI*). The index is made up of two countervailing elements. On the one hand, it builds on information on firms' current and expected technology adoption rates. To move beyond simplistic wishful thinking, we qualify this information by assessing whether and how firms plan to increase their adoption of advanced technologies.

Based on the *DRI*, firms are ranked according to whether they are lagging behind; catching-up with the digital leaders; or indeed moving forward and operating at the frontier (see Kupfer et al. 2019 for details). Figure 3 presents the distribution of these three categories across countries and firm sizes. While digital readiness appears to be limited in our sample, firms that are catching up are more concentrated in Viet Nam and among larger enterprises.

Figure 3: Digital readiness across countries and size groups



Source: Authors' elaboration based on the UNIDO survey "Adoption of Digital Technologies by Industrial Firms".

5.2 Characterizing technology adoption patterns

As already indicated, our empirical exercise entails two steps. First, we focus on inter-firm adoption to gauge the relative effect of internal characteristics and external factors on the incidence of adoption among the firms in our sample. We then move to analyse intra-firm adoption, that is, the intensity of advanced manufacturing technology adoption by firms. For the first step, we employ a dependent variable that captures whether firms' current adoption rate across their various functions reflects the highest possible level of technology adoption. In the second step, the dependent variable reflects a wider spectrum of the state of technology adoption across firms in the sample, allowing for a more granular understanding of the adoption patterns in our sample. Finally, we also distinguish between current adoption patterns and firms' digital readiness. The different nature of the dependent variables used to proxy for technology adoption requires the application of different probability models.

5.2.1 The determinants of inter-firm adoption

Table 1 provides a first characterization of the firm-level determinants of ADP technology adoption in Ghana, Viet Nam and Thailand. Our dependent variable is based on the *DAR_C* indicator. It captures the incidence of adoption by manufacturing firms across the five business functions. The dependent variable is binary and takes the value of 1 when a firm employs technologies that belong to either the third or fourth generation across its business functions. Among the structural characteristics of firms in our sample, only size—proxied here with the number of employees (logs)—appears to be positively and significantly associated with technology adoption. It is worth noting that having access to a fast internet connection (at least

30 Mbit/s) is not significantly associated with digital adoption after controlling for other factors; neither is foreign ownership, in contrast with most firm-level studies of technology adoption.

Table 1: Determinants of ADP technology adoption: probit estimations

VARIABLES	
Age	0.000178
	(0.000305)
Foreign ownership	-0.0114
	(0.0145)
Size	0.0115**
	(0.00495)
Internet speed	0.0158
	(0.0153)
Skilled human capital	-0.000332
	(0.000402)
Investment in capabilities	0.00166
	(0.0199)
Value chain participation	0.0415**
	(0.0168)
Epidemic effects	0.741***
	(0.176)
Observations	650
Industry dummies	YES
Country dummies	YES
Pseudo R^2	0.298

Notes: The table reports marginal effects from the probit regressions. Delta-method standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Source: Authors' elaboration based on the UNIDO survey "Adoption of Digital Technologies by Industrial Firms".

In addition, the results above suggest that firms that participate in a value chain are more likely to adopt new technologies relative to other firms.[8] Investment in a firm's internal capabilities—in the form of investments in R&D, training activities and new equipment or machinery—is not significantly associated with technology adoption.[9] The 'epidemic' variable aims at capturing firms' learning or emulation behaviour vis-à-vis partners and competitors located in the same region and industry (Karshenas and Stoneman, 1993; Battisti et al., 2009).[10] Epidemic effects are positively associated with the adoption of new technologies.

Next, we take advantage of the granularity of the survey to explore whether there are differences in the determinants of technology adoption across the five different business functions identified by the survey. We estimate the determinants of ADP technology adoption for the five functions using a multivariate probit model to account for the possible interrelationships between adoption decisions within firms (Gómez and Vargas, 2012). Results provide further confirmation that larger firms, firms exposed to international trade and production networks, and firms that invest in capability-building activities all appear to be more likely to adopt digital technologies across the various business functions they perform (Table 2).

[8] Value chain participation is defined as a dummy variable that takes the value of 1 when a firm is either: an active exporter of intermediate products; a two-way trader (that is, a firm that exports and imports); or an exporter (or importer) that is currently outsourced from abroad. The definition is adapted from the work of Brancati et al. (2017). There are two differences, however. The first is that whereas their third selection criterion is based on the existence of "long-lasting relationships with foreign companies", we only consider the case of outsourcing relationships. Secondly, our definition of two-way traders only considers those firms whose import and export shares lie above the median import and export shares we observe in their respective countries, whereas Brancati et al. (2017) do not employ import and export thresholds to define two-way traders.
[9] Owing to data limitations, investment in capabilities is defined here as a dummy variable that takes the value of 1 whenever a firm has invested in R&D, training activities or in new machinery and equipment.
[10] Building on the approach of Hollenstein (2004) and Gallego et al. (2015), we define our 'epidemic' variable as the share of other firms that have adopted a technology in the same region and sector.

Table 2: Determinants of advanced manufacturing technology adoption across business functions: multivariate probit estimations

VARIABLES	(1) Supplier relations	(2) Customer relations	(3) Production process management	(4) Product development	(5) Business management
Age	0.00610	-0.00310	0.00735	0.00469	-0.000643
	(0.00803)	(0.00673)	(0.00760)	(0.00640)	(0.00598)
Foreign ownership	0.339*	-0.342	0.240	-0.0423	-0.268
	(0.192)	(0.212)	(0.221)	(0.309)	(0.187)
Size	0.210***	0.200***	0.207**	0.227***	0.196**
	(0.0745)	(0.0687)	(0.0868)	(0.0773)	(0.0794)
Internet speed	-0.112	-0.00167	-0.0291	0.0211	0.561***
	(0.156)	(0.188)	(0.166)	(0.229)	(0.161)
Skilled human capital	0.00369	0.00608	0.0110**	0.00454	0.00309
	(0.00508)	(0.00412)	(0.00437)	(0.00640)	(0.00504)
Investment in capabilities	0.533*	0.555**	0.366	0.492	0.630*
	(0.322)	(0.274)	(0.355)	(0.346)	(0.382)
Value chain participation	0.191	0.248	0.419*	0.704**	0.198
	(0.182)	(0.205)	(0.215)	(0.353)	(0.176)
Observations	650	650	650	650	650
Industry dummies	YES	YES	YES	YES	YES
Country dummies	YES	YES	YES	YES	YES
Rho 2, 1		0.479***	(0.100)		
Rho 3, 1		0.340***	(0.127)		
Rho 4, 1		0.384**	(0.154)		
Rho 5, 1		0.330***	(0.123)		
Rho 3, 2		0.370***	(0.142)		
Rho 4, 2		0.236*	(0.140)		
Rho 5, 2		0.374***	(0.117)		
Rho 4, 3		0.367***	(0.116)		
Rho 5, 3		0.299	(0.185)		
Rho 5, 4		0.157	(0.134)		
Likelihood ratio test of Rho2, 1 = Rho3, 1 = Rho4, 1 = Rho5, 1 = Rho3, 2 = Rho4, 2 = Rho5, 2 = Rho4, 3 = Rho5, 3 = Rho5, 4 = 0: 53.2223***					

Notes*:* The table reports coefficients from the multivariate probit regressions. Delta-method standard errors in parentheses. ***p<0.01, ** p<0.05, * p<0.1

Source: Authors' elaboration based on the UNIDO survey "Adoption of Digital Technologies by Industrial Firms".

Differences do, however, exist. For instance, while positive across the board, participation in a value chain appears to be statistically significant only when considering the firm's activities in the areas of product management and development. This may reflect a learning process whereby firms are exposed to new and improved product specifications by participating in GVCs as importers and suppliers. Investment in internal capabilities, on the other hand, is significantly and positively associated with firms' more 'relational' functions—that is, the maintenance of relationships with suppliers and customers, including the handling of inventories, contracts and sales operations—as well as with the digitalization of internal business operations. Other variables of interest include skilled human capital, which matters particularly for the digitalization and automation of the production process; the availability of a fast internet connection, which is positively and significantly associated with the use of web-based business platforms and AI technology; and foreign ownership, which is positively—albeit weakly—associated with the digitalization of supply chain operations.

5.2.2 The determinants of intra-firm adoption

Our model of intra-firm adoption does not substantially differ from the inter-firm one, for the intensity of adoption is typically thought to depend on similar rank and epidemic effects (Battisti et al., 2009; Grazzi and Jung, 2019). The first notable difference relates to the form of the dependent variable. While we employed a binary variable in Table 1 to study the incidence of technology adoption in our sample, here our dependent variable takes the values 1, 2 and 3, corresponding to the technological generations identified by *DAR_C*, providing a clearer picture on the intensity of adoption across firms. Due to the paucity of data on Industry 4.0 technology adoption, the top two generations are grouped together. Firms belonging to the two extremes of the spectrum may be thought of as, respectively, firms relying predominantly on analogic technology and firms relying predominantly on advanced ICTs and 4.0 technology.

We then estimate the likelihood of falling into a higher (or lower) technological generation as a function of firms' structural characteristics, capabilities and value chain participation. We employ an ordered probit model, which is appropriate when the dependent variable is measured on an ordinal scale (Grazzi and Jung, 2019). Table 3 reports the marginal effects of our independent variables on the likelihood of falling into each of the three categories defined above relative to all the others. It is worth noting that foreign ownership is, once again, negatively associated with the intensity of technology adoption.

Table 3: Technological generations and their determinants: ordered probit estimations

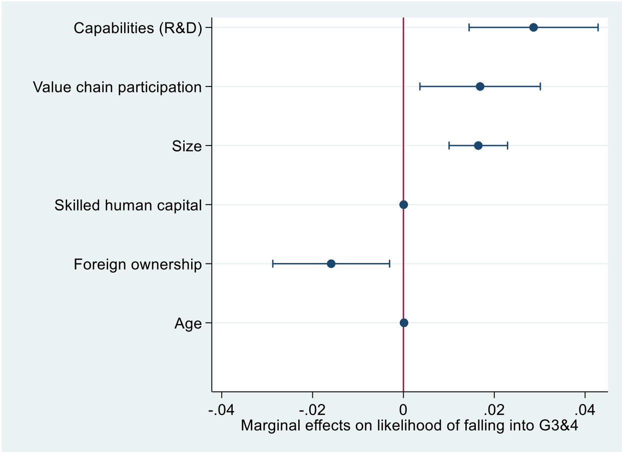
VARIABLES	Technological generation		
	G1	G2	G3&4
Age	-0.000562	0.000400	0.000162
	(0.000916)	(0.000649)	(0.000268)
Foreign ownership	0.0640**	-0.0456**	-0.0185**
	(0.0297)	(0.0213)	(0.00909)
Size	-0.0644***	0.0458***	0.0186***
	(0.0101)	(0.00781)	(0.00412)
Skilled human capital	1.70e-06	-1.21e-06	-4.90e-07
	(0.000877)	(0.000624)	(0.000253)
Investment in capabilities (R&D)	-0.0965***	0.0687***	0.0279***
	(0.0291)	(0.0215)	(0.00914)
Value chain participation	-0.0878***	0.0625***	0.0253***
	(0.0283)	(0.0197)	(0.00983)
Observations	650	650	650
Industry dummies	YES	YES	YES
Country dummies	YES	YES	YES

Notes: The table reports marginal effects from the probit regressions for the three possible outcomes. Delta-method standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Source: Authors' elaboration based on the UNIDO survey "Adoption of Digital Technologies by Industrial Firms".

Taken together, these results suggest that firms' international activities and their investment in building internal capabilities—proxied here by investment in R&D—are positively associated with the intensity of intra-firm digital technology adoption across manufacturing firms in our sample. To facilitate the visualization of these findings, Figure 4 plots marginal effects on the probability of belonging to the highest digitalization category of our main variables of interest.

Figure 4: Average marginal effects on the likelihood of falling into the highest group by technological generation



Notes: The graph depicts coefficients and confidence intervals for the average marginal effects of our variables of interest on the probability of belonging to the group of firms employing technologies that belong to the two highest technology generations.

Source: Authors' elaboration based on the UNIDO survey "Adoption of Digital Technologies by Industrial Firms".

5.2.3 From technology adoption patterns to digital readiness

We are also interested in testing the likelihood of falling into a higher readiness category, conditional on the determinants identified above—firms' skill endowments and capabilities and their exposure to international trade and production. In line with our findings so far, exposure to international trade and production networks, investment in one's internal capabilities—proxied here again by investment in R&D—and firm size are associated with greater levels of readiness on the part of firms (Table 4). A firm's participation in a value chain increases the likelihood that the firm belongs to the group of firms that is moving forward towards the world technology frontier.

A firm's human capital endowment is also positively and significantly associated with digital readiness—albeit with a rather smaller coefficient relative to other covariates—possibly highlighting the enhanced awareness that skilled workers and workers with a STEM background have about new technologies and their importance for firm performance. It is worth noting that younger firms appear to be more likely to be 'digitally ready' relative to their older counterparts, suggesting that they may be less burdened by organizational inertia and technological lock-in (Coad et al., 2016).

Table 4: Determinants of digital readiness: ordered probit estimations

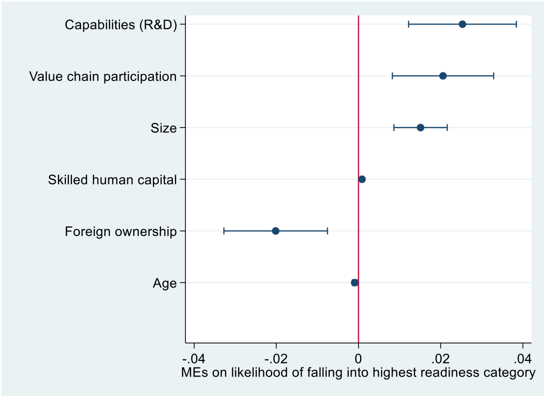
VARIABLES	Digital readiness index (DRI)		
	Lagging behind	Catching up	Moving forward
Age	0.00348***	-0.00262***	-0.000861***
	(0.00122)	(0.000935)	(0.000327)
Foreign ownership	0.0706**	-0.0531**	-0.0175**
	(0.0284)	(0.0216)	(0.00746)
Size	-0.0623***	0.0469***	0.0154***
	(0.0113)	(0.00849)	(0.00396)
Skilled human capital	-0.00335***	0.00253***	0.000829***
	(0.000624)	(0.000499)	(0.000193)
Investment in capabilities	-0.0966***	0.0727***	0.0239***
	(0.0276)	(0.0209)	(0.00797)
Value chain participation	-0.0526*	0.0396*	0.0130*
	(0.0281)	(0.0213)	(0.00721)
Observations	650	650	650
Industry dummies	YES	YES	YES
Country dummies	YES	YES	YES

Notes*:* The table reports marginal effects from the probit regressions for the three possible outcomes. Delta-method standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Source: Authors' elaboration based on the UNIDO survey "Adoption of Digital Technologies by Industrial Firms".

To facilitate the visualization of these findings, Figure 5 plots the marginal effects of our main variables of interest on the likelihood of belonging to the group of firms that are moving forward and operate at the technology frontier according to the digital readiness index.

Figure 5: Average marginal effects on the likelihood of belonging to the group of moving forward firms



Notes: The graph depicts coefficients and confidence intervals for the average marginal effects of our variables of interest on the probability of belonging to the group of catching-up firms.

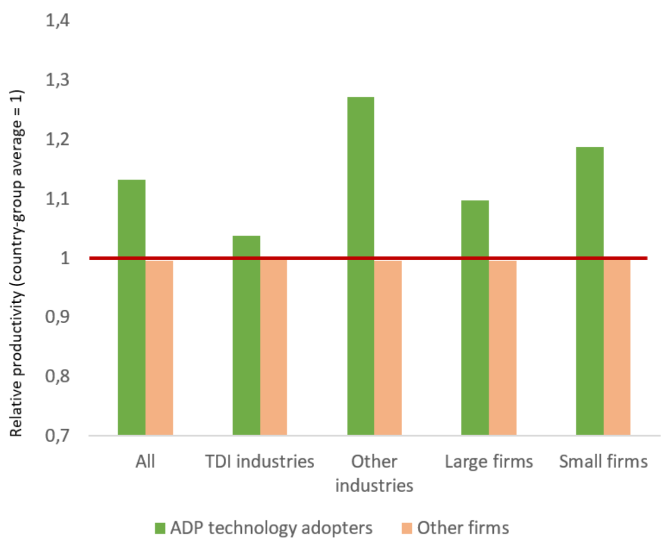
Source: Authors' elaboration based on the UNIDO survey "Adoption of Digital Technologies by Industrial Firms".

5.3 From adoption to firm performance

We are also interested in the relationship between technology adoption, firms' characteristics and capabilities and firm performance. Figure 6 provides some suggestive evidence that firms that adopt ADP technologies tend to be, on average, more productive relative to firms using less advanced digital technology. This holds for firms of different sizes and those that are active in different types of industries.

An empirical test provides further support to this notion. Table 5 presents the results of an OLS regression with labour productivity as the dependent variable. The adoption of ADP technologies is proxied here by a dummy variable that takes the value of 1 when a firm belongs to one of the two groups with a higher digitalization rank. Firms' technological capabilities are positively and significantly associated with labour productivity in our sample. Firms' age is positively associated with productivity, possibly reflecting the accumulation of production or technological experience, but the effect is statistically weak. Firms that belong to a foreign group also appear to be more productive, despite the generally negative association between technology adoption and foreign ownership observed above.

Figure 6: Relative productivity of ADP technology adopters and non-adopters, by size and industry



Notes: ADP is advanced digital production. TDI is technology- and digital-intensive. The figure shows the difference in average productivity level for all firms in the country, by industry and firm size. TDI industries include automotive and auto parts and electronics. Other industries include food and beverages; textile, leather and footwear; plastic and rubber; metal products; and wood and furniture.

Source: Authors' elaboration based on the UNIDO survey "Adoption of Digital Technologies by Industrial Firms".

In line with the existing literature on the impact of ICTs and advanced digital technologies on firm-level performance, the intensity of technology adoption is positively associated with firms' performance, although the significance of the association is weak (Cardona et al., 2013; Aboal and Tacsir, 2018). Firms' performance, however, may itself be the driver of digital technology adoption, as we would expect better-performing firms to be more likely to employ ADP technologies in their operations. For this reason, we also employ an instrumental variable approach (see Columns (3) and (4) below). We instrument a firm's digital adoption by considering the degree of digital technology diffusion within its sector and geographical area.[11] Our finding that a positive and significant relationship exists between digital technology adoption and firms' performance is confirmed when employing a 2SLS estimation.

[11] We test the suitability of our instrument for the 2SLS estimation. The endogeneity test confirms that the instrumented variable should indeed be considered endogenous. The first-stage weak instrument test provides evidence of correlation between the instruments and the instrumented variable.

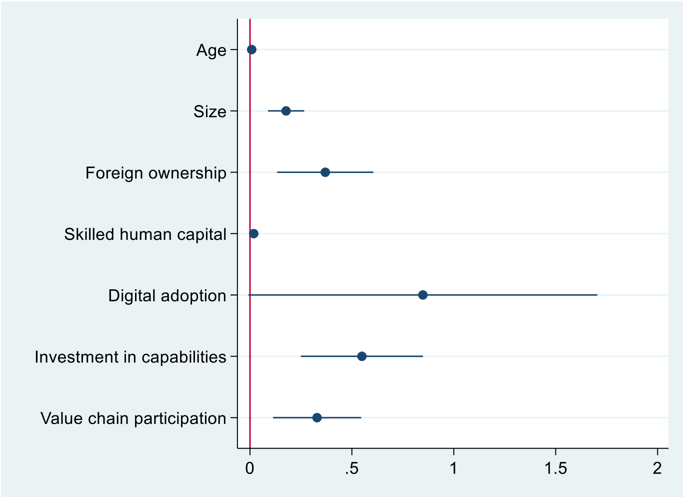
Table 5: Technology adoption, value chain participation and labour productivity: OLS and 2SLS estimations

VARIABLES	OLS		2SLS	
	(1)	(2)	(3)	(4)
Age	0.00864	0.00826	0.00842	0.00807
	(0.00567)	(0.00573)	(0.00557)	(0.00562)
Size	0.169***	0.174***	0.138**	0.146**
	(0.0530)	(0.0532)	(0.0576)	(0.0578)
Foreign ownership	0.345**	0.370***	0.372***	0.387***
	(0.138)	(0.139)	(0.140)	(0.139)
Skilled human capital	0.0188***	0.0187***	0.0193***	0.0191***
	(0.00468)	(0.00479)	(0.00456)	(0.00468)
Adoption of ADP technologies	0.793*	0.832*	2.630*	2.395
	(0.478)	(0.474)	(1.490)	(1.488)
Investment in capabilities	0.539***	0.548***	0.533***	0.539***
	(0.176)	(0.177)	(0.173)	(0.174)
Value chain participation	0.297**	-	0.245*	-
	(0.129)		(0.130)	
Exporter	-	0.238*	-	0.220
Observations	624	624	624	624
Industry dummies	YES	YES	YES	YES
Country dummies	YES	YES	YES	YES
R-squared	0.860	0.860	0.854	0.854

Notes: The dependent variable is labour productivity (sales per worker, in logs). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Value chain participation is also positively associated with labour productivity, although with a slightly weaker statistical significance relative to the other covariates. An alternative specification is presented in Columns (2) and (4). Focussing on firms' exporting activities only, these findings support the positive association between productivity and firms' international activities, although with smaller coefficients and weaker statistical significance (it breaks down in our final specification). This suggests there may be a productivity premium for firms participating in value chains relative to exporting firms. Figure 8 reports coefficients and confidence intervals for our main variables of interest from our preferred specification (Column 1). Our findings are broadly in line with the literature on exporting, value chain participation and firm performance. However, contrary to other studies (Montalbano et al., 2018), we cannot identify the direction of causality due to the cross-sectional nature of our sample and the lack of appropriate instruments to proxy for firms' international activities.

Figure 7: Enablers of productivity in manufacturing firms



Notes*:* The graph plots coefficients and confidence intervals from the regression in Table 5 above, Column (1).
Source: Authors' elaboration based on the UNIDO survey "Adoption of Digital Technologies by Industrial Firms".

6. Concluding remarks

This paper contributes to the ongoing debate on the digitalization of manufacturing in developing and emerging economies. We explore the determinants of digital technology adoption in three developing and emerging industrial economies, Ghana, Thailand and Viet Nam. Our findings suggest that the adoption of advanced digital production technologies in manufacturing remains extremely limited. Firms that adopt advanced digital production technologies are characterized by a larger-than-average size and by an involvement in global value chains. Firms that invest in their own technological capabilities—be it in the form of R&D, training or by purchasing new equipment—also appear to be likelier to adopt new technologies. The same findings apply when we investigate firms' digital readiness rather than their current adoption patterns.

We also consider the relationship between the adoption of ADP technologies and firm performance with a focus on labour productivity. We partly address the endogeneity in the relationship between technology adoption and productivity by employing an instrumental variable approach. In line with the existing empirical literature, our findings suggest that there may be a productivity premium associated with the adoption of advanced digital production technology in manufacturing. Firms that are embedded in a value chain and those that invest in capability-building activities also appear to be more productive, controlling for other covariates.

We are aware of the limitations of our study. Due to the cross-sectional nature of the dataset, we are not able to establish causality in the relationship between firms' characteristics and technology adoption; nor can we establish causality in the relationship between technology adoption and firm performance. Our results therefore serve to identify those firm characteristics that may be more closely related to technology adoption and to derive firm typologies, rather than to establish clear causal relationships. However, we believe that this paper is a valuable contribution to discussions on digitalization in emerging economies, particularly in light of the rather unique nature of the dataset and of the relevance of technology diffusion for economic development.

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Appendix

Annex I. Variable definitions and summary statistics

Table A1 – Summary statistics and definitions of variables used

Variable	Definition	Obs	Mean	Std. Dev.	Min	Max
Labour productivity (logs)	Sales per worker in 2018 (local currency)	630	9.38	3.97	1.84	17.41
Adoption of ADP technologies	Dummy equal to 1 for firms that belong to the two highest categories of indicator *DAR_C*	659	0.03	0.17	0	1
Digitalization status	Categorical variable indicating firms' average digitalization status, taking values 0 to 3	658	1.21	0.48	1	4
Digital readiness index	Categorical variable indicating firms' 'digital readiness', based on their current and expected adoption rates; and on their ongoing digitalization plans and actions	658	1.25	0.50	1	3
Age of the firm	Age (years)	659	16.90	12.73	1	118
Size	Number of employees (logs)	658	4.80	1.27	2.89	9.99
Foreign ownership	Dummy equal to 1 for firms that have at least 10% foreign ownership	659	0.41	0.49	0	1
Internet speed	Maximum speed of a firm's fixed internet connection, taking the value of 0 if a firm does not have access to an internet connection; 1 if a firm has access to a connection of between	659	1.29	0.68	0	2

	30 and Mbit/s; 2 for access to a connection of at least 100 Mbit/s.					
Skilled human capital	Share of employees with a STEM background	651	12.67	17.46	0	100
Investment in internal capabilities	Dummy equal to 1 for firms that have carried out investment in R&D, training or machinery and equipment	659	0.76	0.42	0	1
Capabilities (R&D)	Dummy equal to 1 for firms that have carried out investment in R&D	659	0.29	0.45	0	1
Value chain participation	Dummy equal to 1 for firms that are either exporters of intermediate products; or firms whose import and export shares lie above the median shares in their respective countries; or that are importers or exporters and are also outsourced from abroad	659	0.47	0.49	0	1
Exporter	Dummy equal to 1 if the firm exports	0.58	0.49	0	0	1
Epidemic effects	Diffusion of ADP technologies at the industry and regional level in the sample. For Table 5, epidemic effects are also calculated by specific business function	0.03	0.04	0	0	0.14

Annex II. Overview of technologies and business functions covered in the survey

Table A2—Technologies by business function

Business function	Technology
Supplier relationship	Analog purchase order transmission
	Manual electronic purchase order transmission
	Electronic purchase order transmission
	Electronic handling of inventories
	Real time supply chain management
Product development	Manual drafting
	Computer-aided drafting and design software (CAD)
	Computer-aided design, engineering and manufacturing systems
	Integrated product data management systems
	Virtual development systems
Process management	Analogue systems
	Simple and rigid automation systems
	Full or partial automation systems
	Machine-to-machine (M2M) communication and/or other systems of smart production based on direct communication or data exchange between machines and between machines and components
Customer relationship	Analogue handling of accounts and contracts
	Manual electronic handling of accounts and contacts
	Sales force automation
	Web-based integrated support systems
	Client lifecycle management and control
Business management	Manual (analogue)
	Non-integrated department-specific information systems
	Modular, integrated information systems
	Web-based business management platforms with embedded databases
	Artificial intelligence

Source: UNIDO’s Survey on the Adoption of Digital Technologies by Industrial Firms.

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