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Abstract

The adoption of new technology is a key driver of firm performance and economic development. In this paper, we develop a framework for the firm-level analysis of the adoption of digital technology in developing economies. We investigate whether firms' participation to global value chains (GVCs) can facilitate the adoption of digital technologies. Using a novel database on the adoption of different generations of technology by manufacturing firms in Ghana, Vietnam, and Thailand, we document that the adoption of Industry 4.0 technologies remains extremely limited. We also find that firms' participation to GVCs is an important driver of digital technology adoption, and that adoption is positively associated with firm-level performance.

Keywords: GVCs; Industry 4.0; Technology adoption; Economic development; Capabilities

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1 Introduction

The term Industry 4.0 refers to ‘smart’ manufacturing systems, enabled by the application of the latest wave of digital technologies to industrial production. These technologies include artificial intelligence, cloud computing, big data analytics, and advanced robotics, among others. The emergence of these new technologies is the result of technical progress in information and communication technologies (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 increasing interoperability of different information technology systems (Sturgeon, 2017). Industry 4.0 technologies are poised to re-shape industrial production by expanding the possibilities of production system integration, thanks to incremental changes in hardware, software and connectivity. The main promise of the application of these technologies in manufacturing is enhancing firm performance through the optimization of production processes and product functionality (Niebel et al., 2019).

There is considerable debate on the implications of Industry 4.0 technologies for economic development. According to some observers the diffusion of advanced digital production technologies in developing economies is likely to boost economy-wide productivity and fuel growth. Others question whether new technologies may not, in fact, hinder economic development by reducing the employmentgeneration potential of economic activities, or by diverting their location back towards industrialized countries (Rehnberg and Ponte, 2018; Hallward-Driemeier and Nayyar, 2019; Andreoni and Anzolin, 2019). Moreover, since the adoption of many new digital technologies goes hand in hand with the need for expensive technology services or royalties for the use or development of specific platforms and software, as well as with the development of adequate skills, developing country firms may face increasing challenges to acquire and integrate these technologies within existing industrial plants. Developing countries may thus remain excluded from the potential gains of 4.0 technologies, with the risk of losing access to higher-end markets (Sturgeon, 2017; Piva and Vivarelli, 2017)

In spite of the growing interest in the possible impacts of digitalization on development, the extent to which Industry 4.0 technologies may have diffused in developing economies remains unclear. The empirical evidence which is available is rather aggregate, and mostly focused on the possible implications of automation for job creation. As a result, our understanding of whether and how the adoption of these technologies may differ across firms, sectors, and countries remains extremely limited. The lack of adequate micro-data has so far constrained the investigation of these issues, undermining the possibility to study what drives the diffusion of these technologies in a developing country context. Against this backdrop, we contend that studying the firm-level mechanisms shaping the adoption (or lack thereof) of Industry 4.0 in greater detail would allow to shed light on the patterns of technology diffusion in developing economies, and provide evidence-based insights for the design of innovation and entrepreneurial policies.

This paper contributes to filling this gap. Taking into account the sectoral and firm-level heterogeneity characterizing the industrial structures of developing economies, we propose new indicators for firm-level technology adoption, allowing us to draw a first sketch of the diffusion of Industry 4.0-related technologies in developing economies. Then we move towards identifying the firm-level characteristics associated with the adoption of advanced digital technologies in a developing country context, placing a particular attention on the role of participation into GVCs. The motivation for our focus on GVCs stems from the observation that firms in developing economies are more likely to gain knowledge into frontier technologies through international rather than domestic channels, as the production of Industry 4.0 technologies remains concentrated in a small set of industrialized economies (UNIDO, 2019). Exposure to GVCs may act as one of such channels, as it has been linked to a wider diffusion of knowledge, and to larger opportunities for learning and capability development (Fu et al., 2011; Morrison et al., 2008; Saliola and Zanfei, 2009).

We study these questions by taking advantage of a novel UNIDO database on the adoption of digital production technologies by manufacturing firms in three developing countries—Ghana, Vietnam and Thailand. These countries represent three interesting settings. While Ghana, not unlike other Sub Saharan African countries, has only recently began to integrate within GVCs, Vietnam and Thailand have a longer history of engaging with global production (Amendolagine et al., 2019). The database contains rich information on the adoption of different vintages of digital technologies at a very disaggregated level. Since firms were asked about the technologies employed in specific business tasks, the granularity of the data allows us to explore technology adoption patterns across firms as well as within firms, across the various business tasks they perform.

We find that the adoption of Industry 4.0 technologies is extremely limited in the three countries, suggesting that less than five percent of firms are aware of these technologies or possess adequate digital capabilities to integrate them into their production systems. Relevant differences between different types of firms exist. Still, even once controlling for investments and relevant firm characteristics, firms participating into value chains are significantly more likely to adopt advanced digital technologies. Adopters are also typically larger and invest in capability-building activities, such as R&D, training, and in new equipment and machinery, suggesting that financial and human resources still play an important role in driving digitalization at the firm level. Finally, although the UNIDO data consists so far of a single cross-section and it is thus not possible to test causal claims, our findings suggest the existence of a small productivity premium associated with the adoption of new digital technologies.

The paper is structured as follows. Section 2 provides a review of the three strands of literature we are interested in, namely the literature on technology adoption; firm-level technological capabilities; and value chain participation. Section 3 describes the data, and how it can be used to generate original indicators of technology adoption. In section 4, we put forward our empirical approach to study technology adoption, as well as the impact of adoption on firms' performance. Section 5 discusses the results from the empirical exercises. Section 6 concludes and outlines some directions for future research.

Related literature

Our paper primarily relates to the literature on the firm-level determinants of technology adoption. A large body of empirical work shows that the adoption of new technologies relates to firms' internal resources and the availability of 'intangibles', such as enabling technologies, organizational designs, and skilled personnel (Hollenstein, 2004; Lucchetti and Sterlacchini, 2004; Fabiani et al., 2005; Giunta and Trivieri, 2007; Gallego et al., 2015). The presence of intangible assets ensures that new technologies are successfully implemented, and returns from their adoption fully appropriated (Milgrom and Roberts, 1995; Gomez and Vargas, 2012). While emphasizing the role of firms' internal resources, this line of research also explores the role of learning by emulating peers and competitors in one's own industry or geographical area (Battisti et al., 2009; Grazzi and Jung, 2019).[1] Our paper builds upon these contributions, as we jointly consider firms' internal characteristics and learning effects (at the sectoral and geographical level) as important determinants of technology adoption. However, we extend this framework by drawing insights from two distinct strands of literature.

First is the literature on technological capabilities at the firm-level. While the literature on the determinants of technology adoption uses several indicators to study firms' resources and competencies, it tends to consider these in isolation. Studies of production and technological capabilities, by contrast, highlight the importance of a comprehensive understanding of firms' knowledge bases, skills, and competencies as components of complex bundles that are best understood in association with each other (Lall, 1992; Bell and Pavitt, 1993; Archibugi and Coco, 2004; Fu et al., 2011). Our paper fits in this understanding. Motivated by the persistence of wide differences in adoption patterns between countries and across firms, literature on technological capabilities highlights the importance of learning and absorptive capacities to understand technology adoption. 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. 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 (Lall, 1992; Bell and Pavitt, 1993; Morrison et al., 2008).

Moreover, we take a step further and consider firms' integration within value chains as an important determinant of the decision to take up a new technology. The firm-level literature on GVC participation finds that value chain relationships can enhance the productivity of domestic suppliers and affiliates (Montalbano et al., 2016; Brancati et al., 2017; Del Prete et al., 2017) and facilitate the transfer of knowledge between lead firms and value chain partners (Saliola and Zanfei, 2009; Alcacer and Oxley, 2014).[2] Participation to GVCs may stimulate technology adoption as the result of competition and learning effects. Traders exposed to international competition may opt to digitalize to gain a competitive edge, while relationships with lead firms can stimulate technology adoption through learning processes (Morrison et al., 2008; Alcacer and Oxley, 2014; De Marchi et al., 2018). For instance, subsidiaries of MNCs may gain access to new technologies developed abroad, while suppliers may be pressured by their international buyers to digitalize part of their operations. Thus, in some instances the very possibility of gaining entry to GVCs hinges on digital capabilities. A large

[1] Learning effects are an important feature of early theoretical work on technology adoption. In 'epidemic' models, adoption increases over time as costs and risks fall. As early adopters disseminate information on new technologies, other firms begin adopting them and disclose further information (Mansfield, 1963; Hall and Khan, 2003). More recent work focuses on firms' internal characteristics and their heterogeneity. 'Rank' models postulate that firms adopt new technologies up to the point where the marginal expected gross profit gain from their use equals the marginal expected cost—which hinges on a firm's internal characteristics. Since these are assumed to be distributed unevenly—in contrast with the representative agent assumptions of early epidemic models—the timing of adoption differs from firm to firm (Karshenas and Stoneman, 1993; David, 2011).

[2] Empirical studies investigating whether FDI brings about productivity spillovers in host economies reach similar conclusions, particularly regarding backward linkages (Javorcik, 2004; Farole and Winkler, 2013; Newman et al., 2015)

literature of case studies, however, also points out that value chain relationships are not necessarily beneficial for domestic country firms, as asymmetric power relationships in GVCs may prevent them from upgrading their capabilities (Humphrey and Schmitz, 2002; Gereffi et al., 2005).

Finally, insofar as it considers the relationship between digital technology adoption and firms' performance, our contribution also relates to the empirical literature on the impact of advanced ICT adoption at the firm-level. This literature points out that the adoption of ICTs tends to be associated to a productivity premium across firms, in both developed and developing economies (Arvanitis and Loukis, 2009; Aboal and Tacsir, 2018; Grazzi and Jung, 2019). The mechanisms linking the adoption of advanced ICT technology to firm performance include the availability of faster communication and information processing tools, which decrease internal coordination costs thus facilitating firms' decision-making and reducing information asymmetries (Cardona et al., 2013). Moreover, ICTs might provide the foundation on which businesses innovate, acting as general-purpose technologies (Bresnahan and Trajtenberg, 1995).[3]

2 Data

2.1 The UNIDO survey on the adoption of digital production technologies by industrial firms

Data for this study comes from the firm-level database collected by UNIDO through the *Survey on the Adoption of digital production technologies by industrial firms* carried out in 2019 on a sample of 658 firms operating in selected industrial sectors in Ghana, Thailand and Viet Nam. This survey represents one of the first systematic attempts to collect micro-data to investigate the industrial application of advanced digital production technologies associated to Industry 4.0 in developing and emerging countries (UNIDO, 2019). Data was gathered through face to face interviews based on a structured questionnaire developed in collaboration with the Federal University of Rio de Janeiro. The survey instrument was tailored to the analysis of firms' current and expected patterns of technology adoption, but it covers a wider range of issues such as innovation, skills, location of production, trade, environmental sustainability.

The survey gathered data on a randomly chosen sample of firms with at least 20 employees operating in selected industrial sectors and geographical locations.[4] The locations were identified according to the distribution of industrial production in the country, focusing on regions and urban areas with relatively large presence of manufacturing activities. Since the primary purpose of the UNIDO survey is to gather information on production technologies, the sectors of interest were chosen according to their strategic importance for the individual country's manufacturing sector. In order to better reflect the characteristics of the country's industrial sector, the random sample was also stratified by firm size. Although the resulting sample is not representative of the whole

[3] The empirical studies exploring the impact of Industry 4.0 technologies are understandably fewer. A recent paper on the use of big data analytics by German firms, however, makes a similar argument in suggesting that new practices in analysing data enhance firms' decision-making possibilities, thus supporting innovativeness. It finds that big data analytics is an important determinant in the likelihood of firms commercializing new product innovations (Niebel et al., 2019).

[4] See the Annex for a more detailed description of the sample.

manufacturing sector at country or location level, it still provides useful insights for the analysis of the phenomenon of firm-level diffusion of advanced digital technologies.

Table 1 displays some general characteristics of the sample. The distribution of employment shows that the sample consists mostly of small and medium enterprises: more than 50 percent have less than 100 employees, with almost half of them employing between 20 and 50 people. About 36 percent of surveyed firms operate in medium-high-technology industries [5], while 50 percent operate in low-technology industries, with food representing more than one fourth of firms in the sample.

2.2 A refined picture of technology adoption

Most of currently available firm-level surveys investigating the diffusion of Industry 4.0 technologies concentrate on some advanced digital technologies, asking firms precise questions about the adoption of robots, cloud computing, or additive manufacturing, among others [6]. Collecting information on specific technologies presents some limitations when applied to actors in developing economies, whose industrial structures is characterized by a particularly large heterogeneity (Ferraz et al., 2019). Here, a broad range of production technologies tend to coexist as firms distribute along a wider technological spectrum, displaying relevant structural differences in terms of technological level and capabilities. On one end of this spectrum, there are many firms producing goods and services through traditional production processes, without the use of any digital technology; on the other extreme, few firms for which advanced digitalization is an essential part of the business strategy. In such a context, inquiring only about some specific advanced technologies would fail to adequately represent this heterogeneity, making it difficult to derive useful insights for policy (Ferraz et al., 2019; Kupfer et al., 2019).

Heterogeneity also characterizes the internal structure of the firm, when diverse levels of technological sophistication may be employed at the same time in different activities. Conceiving technology adoption as the application of a uniform technological package into firm's functions could hide the diversity of firms' technological patterns.

Acknowledging heterogeneity as a main feature of the industrial structure in developing economies, the UNIDO survey takes an alternative approach. Following the experience of a firm-level data collection exercise conducted in Brazil in 2017 within the framework of the project Industria 2027,[7], it inquires about the whole range of production technologies possibly employed by manufacturing firms. These production technologies are grouped into different 'technological generations', ordered according to the degree of technological sophistication: from the most simple and analogical ones to the most cutting-edge advanced digital production technologies associated to

[5] We follow the categorization of manufacturing sectors into high-, medium-high-, medium-low and low-technology industries proposed by OECD (2011). High-technology industries (i.e. pharmaceutical, aircraft and spacecraft, medical and optical equipment) are not present in the considered sample.

[6] See for example the European Manufacturing Survey or Eurostat survey ICT usage and e-commerce in enterprises.

[7] For more details on the Industrial 2027 project, see IEL (2018).

Industry 4.0. Thus, the generations of production technologies cover the whole spectrum of technological and digital complexity—in terms of increasing integration, connectivity, and flexibility.

Table 1: Characteristics of the sample

Firms by size group		**Firms by sector**	
20-49	24%	*Medium-high-technology industries*	
50-99	27.2%	Electronics and ICT	16.6%
100-199	15.2%	Automotive and autoparts	19.3%
200-349	12.2%	*Medium-low-technology industries*	
350 and above	21.4%	Plastic and rubber	5.3%
Total	100%	Metals	6.1%
		Low-technology industries	
		Food and beverages	27.8%
		Textile and apparel	18.7%
		Wood and furniture	6.2%
		Total	100%

Notes: All percentages are calculated based on the total number of firms in the sample, i.e. 658. Sectors are defined according to the following ISIC Rev.4 codes: food products, beverages and tobacco (1010 to 1200); textiles, textile products, leather and footwear (1311 to 1520); electronics and Information and Communication Technologies (ICT) (2610 to 2670); automotive and autoparts (2910 to 3091); furniture and wood (1610-1629; 3100); metal products (2410-2599); plastic and rubber (2210-2220). Medium-high-, medium-low and low-technology industries are defined according to the classification of manufacturing industries based on technology proposed by OECD (2011).

In this work, we identify four technological generations (Table 2)[8]. Generation I refer to a pre-digital production system: it includes all types of analogue technologies possibly used in different stages of manufacturing production. The generations above generation I correspond to digital production technologies employed in manufacturing. Generations II and III have been around for as long as numerical control programming systems exist (the late 1950s), although the evolution of devices such as computer-aided-design (CAD) has been exponential in recent years thanks to parametric engines. Generation IV represent the highest level of digital and technological complexity, enabling the integration of the whole production processes. It also includes the most advanced digital applications with 'smart' features , such as real-time interaction and data exchange, robotization, sensorization, big data, artificial intelligence, and communication devices, among others. Most of the advanced digital production technologies that usually fall under the label of Industry 4.0 can be found in this technological generation. Even if it may be imprecise to pair a specific technological generation with a concept such as Industry 4.0, for the purpose of this analysis we approximate Industry 4.0 with generation IV.

[8] Ferraz et al. (2019), Kupfer et al. (2019) and UNIDO (2019) employ a different categorization, with five technological generations. In this paper, we have combined the top two generations.

Table 2: Technological generations

Technological generations	Definitions
I. First generation: analogue production	No digital technologies are used throughout the whole production process (e.g. personal contact with suppliers or via phone; use of machinery that is not micro-electronic based
II Second generation: rigid production	The use of digital technologies is limited to a specific purpose in a specific function and activity (e.g. use of CAD only in product development; use of non-integrated machines operating in isolation)
III Third generation: lean production	Digital technologies involve and connect different functions and activities within the firm (e.g. use of CAD-CAM linking up product development and production processes; basic automation)
IV Fourth generation: integrated and smart production	Digital technologies are integrated across different activities and functions, allowing for the interconnection of the production process (e.g. Enterprise Resource Planning (ERP) systems; fully paperless electronic system). In their most advanced version, digital technologies allow for fully integrated, connected, and smart production processes, where information flows in real-time to support decision-making processes (e.g. digital twins; real-time sensors; machine-to-machine communication; collaborative robots (cobots); decision making with big data and artificial intelligence support)

Source: authors' elaboration based on UNIDO (2019) and Kupfer et al. (2019).

Since specific technical solutions may be required in different activities, the sets of production technologies are also grouped into five business functions: supplier relationship, product development, production management, customer relationships, and business management. In this way, each intersection of technological generations and business functions is associated to a unique set of production technologies (see Table 11 in Appendix). Since surveyed firms choose one set of technologies for each business functions, a firm becomes associated with five (eventually even different) technological generations.

2.3 Measuring technology adoption

The granularity of the information about technologies and business functions in the UNIDO data allows obtaining a refined picture of the patterns of inter- and intra-firm technology adoption. We can start grasping an idea of firm's internal technological heterogeneity by looking at the the distribution of technological generations by business function. Table 3 reveals how, in all business functions, the application of production technologies associated to Industry 4.0 is still limited [9]. The functions 'products development' and 'production management' display a lower share of firms (around 2.5-3 percent) employing Industry 4.0 technologies. This is in line with the results of the Brazilian survey, where relatively more firms were found to be technologically advanced in areas

[9] The statistics on the diffusion of advanced digital technologies presented in Table 3 below can be considered an upper threshold, as what we term generation IV tends to also include advanced ICTs which are not necessarily part of the latest wave of Industry 4.0 technologies.

related to clients and suppliers. This suggests that firms may prioritise the digitalisation of value chains over of its internal activities (Ferraz et al., 2019).

The collected information about the technological solutions adopted in each business function can be used to pair each firm with a unique technological and digital profile, which could serve as proxy for the firm's level of technological and digital sophistication. Although the disaggregation by business functions allows accounting for internal technological heterogeneity and provides a more accurate indication of firm's actual technological and digital maturity than having to rely on only one observation, it poses the challenge of collapsing all information into a unique, synthetic value.

Table 3: Intra-firm adoption of production technologies

Technological generations	Supplier relationship	Product development	Production management	Customer relationship	Business management
I	29.64	31.9	29.51	29.83	31.46
II	53.95	47.92	49.54	57.53	44.22
III	11.7	17.72	17.74	7.91	19.3
IV	4.71	2.46	3.22	4.72	5.01

Notes: All percentages are calculated based on the total number of firms in the sample, i.e. 658.

In this regard, we follow the methodology proposed by Kupfer et al. (2019) and generate the categorical variable *Technology Adoption Rate* (TAR_i) as a synthetic measure of firms' technological and digital level. According to firm's answers in terms of employed technological generation, we assign a score between 1 and 4 to each business function. Arguing that even a technologically advanced firm may not adopt the latest vintage of technology in all its activities, we disregard the smallest score and obtain the following aggregate score for each firm:

$$Sum\ adoption = \sum_{i=1}^{4} f_i - \min(f_i)\ , with\ 4 \leq Sum\ adoption \leq 16 \tag{1}$$

where f_i indicates a business function. Based on where a firm's aggregate score falls within a range of set limit values, we group firms into five categories and generate the categorical variable *TARi* as:

$$TAR_i \begin{cases} 1 = generation\ I\ if\ 4 \leq Sum\ adoption \leq 6 \\ 2 = generation\ II\ if\ 7 \leq Sum\ adoption \leq 9 \\ 3 = generation\ III\ if\ 10 \leq Sum\ adoption \leq 12 \\ 4 = generation\ IV\ if\ 13 \leq Sum\ adoption \leq 16 \end{cases} \tag{2}$$

whose values proxy for firm's average level of technological and digital sophistication. As we are particularly interested in the advanced digital technologies associated with Industry 4.0, we obtain the binary variable *Digital Technology Adoption* as:

$$DTA_i = \begin{cases} 1\ if\ TAR_i = 4 \\ 0\ otherwise \end{cases} \tag{3}$$

where DTA_i takes the value 1 if the firm's aggregate technological and digital level corresponds to generation IV (0 otherwise).

Table 4 presents the composition of the variable TAR_i. Looking at the total sample (column 1), firm-level data confirms the presence of a relevant heterogeneity: different generations of production technologies coexist within industrial structures; at the same time, the concentration of most firms in the lower segments of technological and digital sophistication (generations I and II) produces a very skewed distribution of firms along the spectrum of production technologies, where the diffusion of Industry 4.0 technologies is still very limited (3.4 percent of surveyed firms). Yet, relevant differences can be noticed across countries (columns 2-4). In Ghana only 1.5 percent of surveyed firms can be classified as adopters of most advanced digital technologies, while in Thailand this share raises up to the 5 percent. Looking at the other technological generations, Thailand and Viet Nam display a larger share of firms associated to generations II and III, while in Ghana analogue production technologies (generation I) are predominant. The distribution of technological and digital level also differs according to firm-level structural characteristic such as size and sectors (columns 5-8), as showed by the higher shares of firms associated with the highest technological level in medium-high-technology sectors and among actors with more than 100 employees.

Table 4: Technology Adoption Rate

Technological generations	Total sample	Ghana	Thailand	Viet Nam	MHT industries	Other industries	100≤ employees	100+ employees
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I	25.38	68.53	6.00	7.66	8.05	35.07	36.80	13.40
II	56.69	20.30	67.50	75.86	70.76	48.82	53.41	62.12
III	14.74	9.64	21.50	13.41	16.53	13.74	8.01	21.81
IV	3.19	1.52	5.00	3.06	4.66	2.37	1.78	4.67
Obs.	658	197	200	262	236	422	337	321

Notes: All percentages are calculated based on the number of observations reported in the last row of each column. MHT are medium-high-technology industries, which include electronics and ICTs, autmotive and autoparts (OECD, 2011).

3 Empirical approach and variables

The model that we estimate departs from the premise that a firm will decide to take-up a new technology when the expected gains resulting from adopting a new technology exceed its costs. Firms may benefit from new technologies in several ways. They may, for instance, increase their market share, reduce their processing costs, or make it possible to increase quality and selling prices. Building upon previous empirical work on the firm-level determinants of technology adoption (Karshenas and Stoneman, 1993; Baldwin, 1995; Fabiani et al., 2005; Battisti et al., 2009; Gomez and Vargas, 2012; Gallego et al., 2015), we see the expected returns from digital technology adoption as shaped by a combination of firm-level characteristics (or rank effects) and learning (or epidemic) effects.[10] We estimate the following model:

[10] Building on game-theoretic literature on technology diffusion (Reinganum, 1981; Quirmbach, 1986), some studies suggest including 'stock' and 'order' effects to the model (Karshenas and Stoneman, 1993; Battisti et al., 2009). These refer, respectively, to the observation that the benefit for the marginal adopter may

$$A_i = \gamma_0 + \gamma_1 x_i + \gamma_2 e_i + \gamma_3 c_i + \gamma_4 s_i + \epsilon_i \qquad (4)$$

where *A* indicates the expected return on the adoption of digital technology for firm *i*, x_i is a vector of firm-level variables capturing rank effects, e_i indicates epidemic-learning effects at the sub-national and industry level, and terms c_i and s_i refer to, respectively, country and sector fixed effects. Since digital adoption is a latent variable, which we only observe in our data as a binary outcome, we are unable to directly observe the returns to the adoption of new technology. To proxy for A_i, we use the variable DTA_i (*Digital Technology Adoption*) indicating whether firms employ advanced digital technologies associated to Industry 4.0. The binary nature of our dependent variables suggests the use of a probability (probit) model (Fabiani et al., 2005; Battisti et al., 2009; Gomez and Vargas, 2012). Our estimating equation becomes as follows.

$$\Pr(DTA_i = 1) = \beta_0 + \beta_i GVCparticipation + \beta_1 x_i + \beta_2 e_i + \beta_3 c_i + \beta_4 s_i + \epsilon_i \qquad (5)$$

Our main hypothesis is that firms' exposure to global value chains may be a driver of the adoption of advanced digital technologies. As discussed in the literature review, firms active in GVCs have been found to be more likely to adopt new technologies, be it in the form of new equipment, production standards, or management practices (Saliola and Zanfei, 2009; Baldwin and Yan, 2014; Alcacer and Oxley, 2014; De Marchi et al., 2018). We define GVC participation at the firm level as a binary variable taking 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 proposed definition is adapted from the work of Brancati et al. (2017)[11].

The vector of rank effects (x_i) include other variables capturing the structural characteristics of firms, such as firms' size, their age, and a dummy variable indicating whether a firm is partly foreign-owned. We consider firms size because larger firms tend to have fewer financial constraints. They may be in a better position to withstand the costs associated with investing in new technologies (Kelley and Helper, 1999; Fabiani et al., 2005). Similarly, foreign-owned firms have been found to be early adopters of new technologies (Gomez and Vargas, 2012), even though this effect appears to be more ambiguous in developing countries (Gallego et al., 2015; Aboal and Tacsir, 2018). With regard to the effect of age, there is no clear consensus: if on one hand older firms may be considered more likely to adopt new technologies in light of their experience, on the other hand they may also face higher switching costs relative to newer entrants, and may be more prone to suffer from organisational inertia (Coad et al., 2016).

decrease with an increase in the number of previous adopters (which may act as a counter-weight to any epidemic-learning effect which might be at play); and to the possibility that early adopters benefit from first-mover advantages. We choose not to include these effects due to the lack of time-series data on adoption in our sample. Moreover, both Karshenas and Stoneman (1993) and Battisti et al. (2009) find little empirical support for these effects, and argue that epidemic effects seem to be dominant over stock and order effects.

[11] It has to be noted that our definition present two major differences with respect to what proposed by Brancati et al. (2017): first, 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; second, our definition considers as two-way traders only those firms whose import and export shares lie above the average import and export shares that we observe in their respective countries, whereas Brancati et al. (2017) do not employ import and export thresholds to define two-way traders.

We are also interested in the role of firm-level technological capabilities in shaping technology adoption. Firm-specific differences in the accumulation of capabilities to absorb new knowledge have been identified as important factors that affect the profitability of adopting a new technology. Upgrading towards the most advanced technological generations depends on firms acquiring the necessary capabilities to implement significant technological and organizational changes to effectively integrate new technologies into existing production processes. Technological capabilities enable firms to recognize value in new sources of external information, and consequently to assimilate and integrate them in their operation (Cohen and Levinthal, 1990). Investment in activities such as R&D, the training of human capital, and generally engaging in production can all enhance a firm's knowledge base, helping firms adapt to technical change in the wider economy (Lall, 1992; Bell and Pavitt, 1993). To capture these dimensions of firm-level capabilities, we define a dummy variable taking the value of 1 whenever a firm has invested in R&D and training activities, and 0 otherwise. Moreover, since the adoption of Industry 4.0 may require an upgrade in terms of organizational capabilities, we also add a dummy variable for the introduction of an organizational innovation.

Our model includes epidemic-learning effects (e_i). In line with previous literature, we model epidemic effects as the share of other firms that have adopted Industry 4.0 technology in a firm's own region and industry (Hollenstein, 2004; Gallego et al., 2015). Potential adopters may have trouble estimating the costs and benefits associated with a new technology. These difficulties are greater when new technologies are developed outside the boundaries of the user firm, as is the case with Industry 4.0 technologies in developing countries. Learning from prior adopters can reduce uncertainty and, consequently, raise the expected profitability of technology adoption (Kelley and Helper, 1999). With the passing of time, as the costs associated with gathering information about the technology decrease, more and more firms may choose to adopt the technology during any period, leading to an increasing rate of adoption (Hall and Khan, 2003).

Finally, we include country (c_i) and sector (s_i) fixed effects to account for the heterogeneous characteristics of the environments wherein firms operate. Country and industry characteristics are likely to influence the decision to adopt new technologies by specifying, respectively, institutional and local market conditions, and the industry-specific technological opportunities that firms face at any point in time (Klevorick et al., 1995). The innovation system within which a firm is embedded can also specify different structures of incentives with regard to the adoption of new technologies (Pietrobelli and Rabellotti, 2011).

We are also interested in understanding whether firms' adoption of digital technologies is associated with higher firm performance. Having examined the determinants of adoption, it is important to understand whether the take-up of new technologies is associated with an improvement in performance. To do so, we focus on the relationship between technology adoption and labour productivity. We estimate the following equation, with subscript *i*, *j*, and *h* indicating, respectively, firm, country and industry:

$$y_{ijh} = \beta_0 + \beta_{jh} + \beta_1(DTA)_{ijh} + \beta_2 X_{ijh} + \epsilon_{ijh} \tag{6}$$

where *y* denotes labour productivity measured as sales per employee, technology adoption takes the form of the binary variable DTA_i (*Digital Technology Adoption*), and *X* is a vector of firm characteristics including their structural characteristics, 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.

Identifying the causal effect of digital technology adoption on firm-level performance is challenging, because the adoption of new technologies is not randomly distributed across firms. Firms' performance may be the driver of digital adoption, as better-performing firms may be more aware of the potential benefits of digital technologies, and have greater resources at their disposal to purchase and effectively use new tools and software relative to their less efficient counterparts. Endogeneity might also arise from the dependent and independent variables being driven by unobservable factors. Due to data limitations, we are unable to apply panel techniques and adequately control for eventual endogeneity. The results we obtain are therefore interpreted as indicating conditional correlation rather than causality.

Table 5 provides an overview of the main variables employed in our empirical analysis and their summary statistics.

Variable	Description	Obs.	mean	sd	min	max
Technology Adoption Rate (TAR)	Categorical variable with values ranging from 1 to 4, capturing the average level of technological and digital sophistication of firms					
TAR, generation I	Dummy variable equal to 1 for firms with an average level of technological and digital sophistication corresponding to generation I	658	0.254	0.436	0	1
TAR, generation II	Dummy variable equal to 1 for firms with an average level of technological and digital sophistication corresponding to generation II	658	0.567	0.496	0	1
TAR, generation III	Dummy variable equal to 1 for firms with an average level of technological and digital sophistication corresponding to generation III	658	0.147	0.355	0	1
TAR, generation IV	Dummy variable equal to 1 for firms with an average level of technological and digital sophistication corresponding to generation IV	658	0.032	0.176	0	1
Digital Technology Adoption (DTA)	Dummy variable equal to 1 for firms which have adopted Industry 4.0 technology	658	0.032	0.176	0	1
Labour productivity	Sales per worker (in USD) in 2018 (logs)	630	9.404	2.432	0.370	15.281
GVC participation	Dummy variable equal to 1 for firms that either: export intermediates; or that are two-way traders, whose import and export shares are ≥ than the average shares in their country; or that are importers or exporters, and are also outsourced from abroad	658	0.372	0.483	0	1
Investment in capabilities	Dummy variable equal to 1 for firms that have invested in R\&D, training activities, or in new machinery and equipment	658	0.764	0.425	0	1
Size	Dummy equal to 1 for firms with more than 99 employees	658	0.488	0.500	0	1
Foreign ownership	Dummy equal to 1 for firms with at least 10% foreign ownership	685	0.415	0.493	0	1
Epidemic effects	Share of other firms adopting Industry 4.0 technologies within a firm's region and industry	658	0.032	0.049	0	0.231
Technological innovation	Dummy variable equal to 1 if a firm has carried out a technological innovation, new to the firm or the market	658	0.604	0.489	0	1
Internet speed	Dummy variable equal to 1 if a firm has access to a broadband connection	658	0.429	0.495	0	1
Human capital	Share of workers with a STEM background	650	0.122	0.165	0	1
Age	Years in operation	658	16.915	12.743	1	118
Age (logs)	Years in operation, logs	658	2.674	0.665	0.693	4.779
Sector	Food and beverages; textiles and apparel; electronics and ICT; automotive and autoparts; furniture and wood; metal products; plastic and rubber					
Country	Ghana; Thailand; Viet Nam					

4 Results and discussion

4.1 Characterizing inter-firm technology adoption

Table 6 reports marginal effects from estimating Probit equation (5) on our binary adoption variable, DTA_i. Results from our full specification are reported in column (3). We find that firms' participation to GVCs is positively and significantly associated with the adoption of Industry 4.0 technologies. After controlling for other firm-level characteristics, being part of a global value chain is associated with a 3 percentage points higher probability of adopting advanced digital technologies. Our epidemic variable, reflecting the degree of diffusion of Industry 4.0 technologies within a firm's own region and industrial sector, is also positively associated to technology adoption (at the 10% level). This suggests a role for processes of learning, or emulation, vis-`a-vis peers and competitors in stimulating the adoption of new technologies.

Table 6: Determinants of digital technology adoption: probit estimations

	(1)	(2)	(3)
GVC participation	0.0342***	0.0327***	0.0326***
	(0.0155)	(0.0151)	(0.0153)
Foreign ownership	-0.0101	-0.0117	-0.00927
	(0.0147)	(0.0139)	(0.0149)
Age (logs)		0.0129	0.00929
		(0.0106)	(0.0105)
Size		0.0236*	0.0235
		(0.0141)	(0.0153)
Epidemic effects			0.197*
			(0.115)
Investment in capabilities			0.0106
			(0.0194)
Human capital			-0.0270
			(0.0418)
Technological innovation			0.00993
			(0.0154)
Internet speed			0.0169
			(0.0166)
N	658	658	647
Sector dummies	YES	YES	YES
Country dummies	YES	YES	YES

The table reports marginal effects from the ordered probit regression
Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Among the other structural characteristics, firms' size, investment in capability-building activities, and having access to a fast internet connection are all positively but not significantly associated with digital adoption after controlling for other factors. Similarly, a firm's age and being a technological innovator are positively, but not significantly associated with digital technology adoption. Foreign ownership is negatively, although not significantly associated with the adoption of digital technologies. This finding resonates with firm-level studies of technology adoption in developing economies, which find either a neutral or negative relationship between foreign ownership and the take up of new technologies (Gallego et al., 2015; Aboal and Tacsir, 2018).

The industrial structures of developing economies such as Ghana, Thailand and Vietnam are characterized by a high degree of heterogeneity. Within the same industry, firms employing Industry 4.0 technology co-exist with firms using previous vintages of technology. Understanding technology adoption patterns thus requires considering a wider spectrum of firms, belonging to different technological generations (see Section 3). To provide further evidence into the drivers of inter-firm technology adoption across the entire range of firms in our sample, we take advantage of the categorical nature of the TAR variable and implement an ordered probit regression where the dependent variable takes values 1, 2, 3, and 4, these corresponding to the four technological generations.

Ordered probit models are appropriate when the dependent variable is measured on an ordinal scale. Ordered models are premised on the idea that there is a latent, continuous variable underlying the ordinal categories we observe, which is a linear function of a set of regressors and an error term assumed to be normally distributed. In this case, the latent variable can be thought as a metric of the technological prowess of firms in our sample: firms belonging to the two extremes of the spectrum are, respectively, firms relying predominantly on analogue technology; and firms relying predominantly on Industry 4.0. Ordered models identify a number of cut points, which partition this function into a series of regions. Each of the categories 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 the simple probit model.

Table 7 reports the average marginal effects of our independent variables on the likelihood of falling into each of the four categories defined above, relative to all the others.

GVC participation is positively and significantly associated to a firm's membership in the category characterised by the highest level of technological sophistication. Consistent with the findings of previous micro-level studies (Kelley and Helper, 1999; Battisti et al., 2009), size is also positively and significantly associated with the adoption of Industry 4.0 technologies, even though it appears to be have an even larger association with the adoption of ICTs. Firms' investments in capability-building activities appear to be also positively and significantly associated with digital technology adoption. Investments in R&D, training or new machinery increase the likelihood that a firm would fall into the highest technology adoption group by approximately 2 percentage points. We find that epidemic learning effects are positively and significantly associated with the adoption of Industry 4.0 technology at the firm level.

Table 7: Determinants of digital technology adoption: ordered probit estimations

	(1) Generation I	(2) Generation II	(3) Generation III	(4) Generation IV
GVC participation	-0.0753***	-0.00594	0.0559***	0.0254***
	(0.0235)	(0.00573)	(0.0174)	(0.00918)
Age (logs)	0.00169	0.000133	-0.00125	-0.000568
	(0.0183)	(0.00144)	(0.0136)	(0.00616)
Size	-0.103***	-0.00808	0.0761***	0.0346***
	(0.0218)	(0.00748)	(0.0167)	(0.00891)
Foreign ownership	0.000125	0.00000983	-0.0000925	-0.0000420
	(0.0225)	(0.00178)	(0.0167)	(0.00760)
Epidemic effects	-0.663***	-0.0523	0.492***	0.223***
	(0.198)	(0.0501)	(0.149)	(0.0760)
Investment in capabilities	-0.0713***	-0.00562	0.0529***	0.0240**
	(0.0258)	(0.00580)	(0.0201)	(0.00953)
Human capital	-0.144*	-0.0114	0.107*	0.0486*
	(0.0758)	(0.0113)	(0.0556)	(0.0263)
Technological innovation	-0.0296	-0.00233	0.0219	0.00997
	(0.0207)	(0.00268)	(0.0154)	(0.00723)
Internet speed	-0.0108	-0.000850	0.00800	0.00364
	(0.0223)	(0.00189)	(0.0165)	(0.00757)
N	647	647	647	647
Sector dummies	YES	YES	YES	YES
Country dummies	YES	YES	YES	YES

The table reports marginal effects from the ordered probit regression Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Results for the inter-firm models reported in tables 6 and 7 are qualitatively similar. Taken together, these results highlight that firms participating to GVCs are significantly more likely to integrate Industry 4.0 technologies within their operations. While the data does not allow us to investigate the possible mechanisms driving this relationship in detail, our findings provide evidence that GVCs can act as conduits for the diffusion of technology in developing economies, corroborating other sources of micro-level evidence (Saliola and Zanfei, 2009; Alcacer and Oxley, 2014). In line with previous studies (Battisti et al., 2009; Gallego et al., 2015), we also find some evidence pointing to the relevance of epidemic-learning effects in shaping adoption decisions among firms in our sample.

Results for other rank effects are somewhat less conclusive. Size and investments in capability-building activities are positively associated with the adoption of digital technologies, as we would expect, but the significance of these associations is less robust. That the effects of foreign ownership are ambiguous resonates with previous work, and indicate that foreign investment does not act, in the main, as a channel for technology transfer in the countries we are studying. Finally, we find that older firms do not appear to be more likely to adopt new technologies relative to their younger counterparts, suggesting that inertia, and the costs of switching to a new technology, may take precedence over any role which production and technological experience might play (Coad et al., 2016).

4.2 Characterizing intra-firm adoption

In Section 3, we document the existence of heterogeneity not only across firms, but also within them. Different vintages of technology tend to co-exist within the same firm at the same time. Given the costs involved in purchasing and absorbing new technologies, it is unlikely that firms in developing economies would choose to digitalize the entirety of their operations at once. We therefore expect that firm-level characteristics affect intra-firm adoption decisions in different ways. A novel contribution of this work is that we can explore whether the determinants of technology adoption differ across firms' business functions. While we employ the same set of explanatory variables to address this question, the notable difference relates to our dependent variable. We take advantage of the granularity of the data and focus on the adoption of most advanced technologies associated to Industry 4.0 at the level of specific business functions (see Table 3).

In Table 8 we estimate the determinants of digital technology adoption for the five business functions identified in the survey. Since our data provides information on technology adoption for each of these functions, we employ a multivariate probit model. A generalization of the bivariate probit model, multivariate probit regressions allow for the existence of systematic correlations between adoption choices (Cappellari and Jenkins, 2003; Gomez and Vargas, 2012). Results provide further evidence that rank effects, such as firm size, and epidemic effects remain important factors in explaining intrafirm adoption patterns. Correlations between the five adoption decisions are reported at the bottom of Table 8. The LR test is significant, suggesting that the take-up of digital technologies for the different business functions we study might be complementary.

While positively associated to technology adoption across the various functions, GVC participation appears to be statistically significant only when considering firm's activities in the areas of production process management and product development. This finding might reflect a learning process whereby firms are exposed to new production processes, industrial standards and product specifications by engaging into GVCs as importers and suppliers. This finding resonates well with literature pointing to the significance of value chain relationships in stimulating the upgrading of products and production processes by manufacturing firms in developing economies (Humphrey and Schmitz, 2002; Alcacer and Oxley, 2014; Ponte et al., 2019).

Our results also qualify our results on the role of foreign ownership in the adoption of new technologies. Foreign ownership is associated to the digitalization of a firm's relationships with suppliers, with the use of digital tools and applications for the handling of inventories and contracts. Firms that are partly or fully foreign-owned are likely to maintain frequent contacts with suppliers, domestically and abroad, which would incentivize the take up of digital technologies. Similarly, a firm's investment in internal capabilities is more closely associated with firms' relational functions, and with the digitalization of internal business operations. Other variables of interest include the availability of a fast internet connection, which is positively and significantly associated with the use of web-based business platforms and artificial intelligence; and the implementation of organizational innovations, which is positively associated with the digitalization of supply chain operations.

Table 8: Determinants of digital technology adoption: multivariate probit estimations

	"External" functions		"Internal" functions		
	Relations with suppliers	Relations with customers	Process management	Product development	Business management
GVC participation	0.0697	0.269	0.388*	0.448**	0.207
	(0.195)	(0.176)	(0.207)	(0.222)	(0.166)
Age (logs)	0.0840	0.0357	0.218	0.140	0.195*
	(0.140)	(0.149)	(0.214)	(0.207)	(0.106)
Size	0.487**	0.534**	0.152	0.656***	0.233
	(0.214)	(0.194)	(0.209)	(0.242)	(0.181)
Foreign ownership	0.361**	-0.227	0.307	-0.0412	-0.112
	(0.210)	(0.171)	(0.193)	(0.246)	(0.182)
Investment in capabilities	0.455	0.512*	0.302	0.649*	0.611*
	(0.282)	(0.317)	(0.331)	(0.389)	(0.366)
Human capital	0.0456	0.492	1.128**	0.252	0.287
	(0.557)	(0.422)	(0.509)	(0.749)	(0.492)
Technological innovation	0.366*	-0.0287	0.273	0.102	0.176
	(0.191)	(0.202)	(0.242)	(0.241)	(0.187)
Internet speed	-0.124	-0.176	-0.108	-0.0931	0.469**
	(0.172)	(0.181)	(0.204)	(0.210)	(0.183)
Epidemic effects	1.204	2.439*	2.368	3.657**	2.488**
	(1.183)	(1.320)	(1.911)	(1.746)	(1.179)
N			647		
Country dummies			YES		
Sector dummies			YES		
Rho 2,1			0.455*** (0.125)		
Rho 3,1			0.455*** (0.133)		
Rho 4,1			0.577*** (0.134)		
Rho 5,1			0.291** (0.114)		
Rho 3,2			0.506*** (0.135)		
Rho 4,2			0.458*** (0.170)		
Rho 5,2			0.482*** (0.152)		
Rho 4,3			0.162 (0.143)		
Rho 5,3			0.425*** (0.140)		
Rho 5,4			0.245 (0.177)		
LR test of Rho 2,1 = Rho 3,1 = Rho 4,1 = Rho 5,1 = Rho 3,2 = Rho 4,2 = Rho 5,2 = Rho 4,3 = Rho 5,3 = Rho 5,4			chi2(10)=67.71 Prob>chi2=0.0		

The table reports coefficients from the multivariate probit regressions. The "epidemic" variables are function-specific. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.3 From digital technology adoption to firm performance

We are also interested in the relationship between the adoption of Industry 4.0 and firm performance. Table 9 reports results from the labour productivity equation. These confirm that digital technology adoption is positively related to firm-level performance. The adoption of digital technologies is proxied by our dummy variable *DTA*, taking the value of 1 when a firm belongs to the group characterized by the highest digitalization rank. In line with results from the empirical, micro-level literature on the impact of ICTs and digital technology on firm-level performance in developing economies (Cardona et al., 2013; Aboal and Tacsir, 2018), our results highlight that the adoption of digital technologies is associated with a productivity bonus among manufacturing firms in the Ghana, Vietnam and Thailand. The association, however, is only significant at the 10% level. Among our control variables, we find that firm size, investment in capabilities, foreign ownership, and technological innovation are positively and significantly associated with labour productivity. Firms' participation to a value chain is positively but not significantly associated with labour productivity.

Table 9: Digital adoption and productivity

	(1)	(2)	(3)
Digital technology adoption	1.018**	0.928*	0.889*
	(0.498)	(0.489)	(0.461)
Age		0.0148**	0.0125**
		(0.00649)	(0.00589)
Foreign ownership		0.453***	0.402***
		(0.140)	(0.140)
Size		0.384***	0.325**
		(0.126)	(0.128)
Human capital			0.566***
			(0.171)
Investment in capabilities			0.545***
			(0.179)
GVC participation			0.0649
			(0.140)
Technological innovation			0.382***
			(0.134)
N	630	630	630
Sector dummies	YES	YES	YES
Country dummies	YES	YES	YES

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5 Concluding remarks

Our paper draws on novel micro-level data to contribute to the ongoing debate on the digitalization of manufacturing in developing economies. We provide new evidence that the diffusion of Industry 4.0 technologies remains extremely limited in the three countries we study, although differences exist between countries and industries. Adoption rates are higher in Thailand than they are in Vietnam and Ghana. The same observation applies to technology-intensive sectors relative to the rest. Yet across all countries and industrial sectors, less than 5 percent of surveyed firms are currently adopting the most advanced generation of digital technologies in all the business tasks that they perform. To the extent that these countries are representative of other economies at similar levels of development, our findings would strongly suggest that Industry 4.0 technology is yet to undergo a process of diffusion in the manufacturing sectors of developing countries.

Our findings also suggest that there is a significant degree of heterogeneity in adoption patterns among different types of firms. The firms that do adopt advanced digital production technologies are characterised by their involvement in GVCs. Firms that invest in their own technological capabilities— -be it in the form of R&D, training or by purchasing new equipment—and larger firms also appear to be likelier to adopt new technologies. These findings are in line with literature on the firm-level determinants of technology adoption, which points to the importance of 'rank' effects. Our results also resonate with studies on the role of GVCs as conduits of technology diffusion, particularly in low-income countries. A limitation of this study, however, is that our GVC participation indicator falls short to account for differences in patterns of value chain governance (Gereffi et al., 2005; Ponte et al., 2019). Exploring this issue would require greater qualitative information on the types of relationships entertained by local firms with their international clients and suppliers.

We also consider the relationship between the adoption of digital technologies and firm performance, with a focus on labour productivity. In line with the existing empirical literature on the impact of advanced ICT on productivity, our findings suggest that there is a small productivity premium associated with the adoption of advanced digital production technology in manufacturing. Due to the cross-sectional nature of the data, we are not able to establish causality in the relationship between digital technology adoption and firm performance; nor in the relationship between GVC participation and technology adoption. Despite this limitation, the analysis points to a significant relationship that needs to be studied in greater detail.

Our findings provide some insights for the design of technology and entrepreneurial policies in developing economies. The observation that firms' international linkages play an important role in explaining technology adoption patterns certainly corroborates policy efforts which aim at supporting the internationalization of domestic firms. Moreover, the relevance of investments in upgrading the internal resources and competences of firms provides support to policies aimed at easing financial constraints for innovation and production activities, but also to education policies aimed at raising the skill level of workers and managers in developing economies. The heterogeneity we find within each industrial sector we study, however, suggests exercising a degree of caution when designing incentive schemes, as fully horizontal approaches might not be able to target the actors with the greater chances of success.

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Annex

Country sample composition

The UNIDO surveys conducted in 2019 in Ghana, Thailand and Viet Nam employed a uniform probability sampling procedure - a proportional probabilistic stratified sampling - to define each county sample. In case of a small sample, this is the most recommended sampling procedure to obtain unbiased estimates with some known level of precision, even for subgroups of the considered population. This procedure requires the specification of three parameters: (i) the size of final sample; (ii) the margin of error; (iii) the confidence level. Out of three parameters, two must be defined, while the third one remains as the adjustment variable. In the UNIDO surveys conducted in 2019 the sample size was given (200 firms in Ghana, 250 in Thailand and Viet Nam) and the confidence level was set at 90 percent. The consequent margin of error was between 9 and 10 percent, depending on the country (considering only sector stratification).

The sample was stratified by location, industrial sector, and firm size. In terms of location, the 2019 UNIDO focused on the main urban centers or regions with large presence/relevance of manufacturing activities. In Ghana and Viet Nam the data collection concentrated on some economically prominent regions (for Ghana: Great Accra and Ashanti; for Viet Nam: Ha Noi and Ho Chi Minh City), while in Thailand the focus was on the provinces part of or close to the Eastern Economic Corridor (Chachoengsao, Chonburi and Rayong). In terms of industrial sectors, in Thailand and Viet Nam the survey concentrate on (ISIC Rev.4 codes): food products, beverages and tobacco (1010 to 1200); textiles, textile products, leather and footwear (1311 to 1520); electronics and Information and Communication Technologies (ICT) (2610 to 2670); automotive and autoparts (2910 to 3091). In Ghana the sectors of electronics and ICT (2610 to 2670) and automotive and autoparts (2910 to 3091) were excluded due to their extremely limited presence and other industries more relevant for the country were considered, such as furniture and wood (1610-1629; 3100); metal products (2410-2599); plastic and rubber (2210-2220). The stratification by firm size (measured as number of employees) was defined to reflect the features of the industrial sector in each country (i.e. average and median firm size). However, as the primary concern of the survey is to gather information on the diffusion and use of advanced digital production technologies, it was decided to set a lower threshold for firm size, this being a minimum of 20 employees. Although this implies the exclusion of a large number of enterprises operating in a developing economy, micro and very small entrepreneurial actors are less likely to be adopting advanced digital technologies, and would have not added relevant information on the process of upgrading towards advanced technologies. In addition, large firms were oversampled by setting a binding constraint of no more than 50 percent of small companies in each sector. Table 10 summarizes the main characteristics of each country sample

Overview of technologies and business functions covered in the survey

When asking about employed production technologies, the UNIDO survey questionnaire does not give firms a binary option, such as if they are adopting or not a specific advanced digital technology. Instead, since different and specific solutions may be required for the different activities performed in each business function, firms can select one among five alternative sets of technologies ordered according to the degree of technological and digital sophistication (i.e. by technological generation). Each cell of Table 11 specifies the sets of production technologies likely to be employed in a specific business area for a given technological generation. In this way, each firm ends up being associated with five sets of production technologies.

Table 10: Country sample composition

Ghana	#	%	**Thailand**	#	%	**Viet Nam**	#	%
			Location					
Ashanti	62	31.5	Rayong	74	37.0	HCMC	74	28.4
Great Accra	135	68.5	Chonburi	83	41.5	Ha Noi	83	31.8
			Chachoengsao	43	21.5			
			Firms by employment category					
20-50	100	50.8	20-50	21	10.5	20-50	37	14.2
50-199	58	29.4	50-199	102	51.0	50-199	119	45.6
200-349	16	8.1	200-349	25	12.5	200-349	39	14.9
350 and above	23	11.7	350 and above	52	26.0	350 and above	66	25.3
			Firms by sector					
Food and beverages	50	25.4	Food and beverages	60	30.0	Food and beverages	73	28.0
Textile and apparel	31	15.7	Textile and apparel	26	13.0	Textile and apparel	66	25.3
Wood and furniture	41	20.8	Electronics and ICT	46	23.0	Electronics and ICT	63	24.1
Plastics and rubber	35	17.8	Automotive	68	34.0	Automotive	59	22.6
Metal products	40	20.3						
Obs.	197		Obs.	200		Obs.	261	

Notes: Percentages are calculated based on the total number of firms surveyed in each country. Sectors are defined according to the following ISIC Rev.4 codes: food products, beverages and tobacco (1010 to 1200); textiles, textile products, leather and footwear (1311 to 1520); electronics and Information and Communication Technologies (ICT) (2610 to 2670); automotive and autoparts (2910 to 3091); furniture and wood (1610-1629; 3100); metal products (2410-2599); plastic and rubber (2210-2220).

Table 11: Technological generations and business functions

	Businessfunctions				
Technological generations	Supplier relationship	Product development	Production management	Customer relationship	Business management
GIV: Integrated production	Digitalsystems forprocessing ordersstocks stocks, real-time web-services	Integrateddata productsystem (PDMand/orPLM, dataanalysis), virtualdevelopment systems(AR,virtual manufacturing, productsimulation)	Computerizedand integrated processexecution system(RFID,QR), M2Mcommunication systems,advanced automation (cobots,3Dprinting)	Onlinesupport forsalesand after-sales (mobileapp, customerdata analytic,online monitoringof productuse,AI)	Integrated platformto supportdecision making,business analysis(advanced ERP,datawarehouse, bigdata,AI)
GIII: Lean production	Automated electronic transmission oforders (email,EDI)	Integrated systemofdesign andproject engineering (CAD-CAM, CAE,CAPP, 3 Dmodelling)	Partiallyof fully integrated processes (CAM,PLC)	Automated devicesto supportsales (simpleCRM, customer database)	Enterprise resource management infewareas (ERP)
GII: Rigid production	Manual electronic transmission oforders (email)	Stand-alone computer-aided projectsystem (CAD, software2D/3D modelling)	Stand-alone andsimple automationwith disconnected machines (CNC)	Manualelectronic contact (spreadsheet registry, email)	Information systemsby areor department
GI: Analog production	Manual transmission oforders (personal contact, telephone)	Manual generation ofdesigns (2 Dor3D drawingsin 2 dspace)	Nonmicro- electronic based machinery	Manualhandling ofcontacts (personal contact, telephone)	Nosoftware support tobusiness management

Notes: Nor a computer not an Internet connection (even mobile) is required to perform any of the business functions in generation I. The use of a computer is required in all business functions for the technological levels between generation II and IV. An Internet connection is needed to employ the technologies associated with generation IV, while it is not necessary in business functions for generation III or below. Industry 4.0 technologies are associated with generation IV.

Source: authors’ elaboration based on UNIDO (2019) and Kupfer et al. (2019).