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Adoption of advanced digital technologies in developing countries: learning from process innovation

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Abstract

Industrial upgrading requires companies to build the necessary capabilities to achieve gains in their production efficiency. Developing countries face additional constraints due to the presence of informal sectors and the lack of diversification in the economic structure. Based on this premise, we address issues related to the introduction of advanced digital technologies in manufacturing (hereafter Industry 4.0 technologies) in developing countries. As no primary data on Industry 4.0 are available, we turn our focus on new process and technology adoption and conduct a systematic review of empirical studies on technology adoption and its impact. We then analyse data from innovation surveys and World Bank Enterprise Surveys for a number of developing countries in Latin America, Africa and Asia.

Keywords: Industry 4.0; new processes, developing countries, innovation

JEL Classification: L6, L8, O31, O33, O52

1 Introduction

Today's new technological capabilities are poised to deepen digital innovation and transformation, ushering in what has been called the Fourth Industrial Revolution, following the previous three revolutions, namely steam-powered mechanical production (1780s); electrically powered mass production (1870s); and the introduction of electronically-based automated production since the 1960s, which differs from the current fourth wave in terms of higher costs and lower computational power and intelligence interconnectivity (OECD, 2017, p. 27). The label 'Industry 4.0' is used interchangeably (and inaccurately) to describe the policies of diffusion and adoption of these technologies and the set of technologies themselves. Reports by consulting companies list several trends and technologies that are driving the rise of Industry 4.0: the ubiquitous adoption of mobile devices and the development of technologies such as big data analytics, the Cloud, algorithmic management, 3D printing, quantum computing, smart robots, artificial intelligence (AI), the internet of things (IoT), blockchain, system simulation and virtual/augmented reality (Berger, 2016; BCG, 2015a; Deloitte, 2016; PwC, 2018). According to Santiago "*Nine technologies lie at the core […]: robotics, big data, augmented (virtual) reality, additive manufacturing (3-D printing), cloud computing, cybersecurity, Internet of Things (IoT), systems integration and simulation*" (Santiago, 2018, p. 2). Data has allegedly replaced 'steam' as the fuel of this transformation, becoming the main source of innovation and value creation. In an article critical of the oligopolistic asset of the data economy, The Economist refers to data as '*the oil of the 21st century*'. Data and data analytics will become the main lever of global competition, as they foster innovation in both manufacturing and services and are contributing to an increasing convergence between the two ('servitization'). According to Weber (2017), whether a country is only an exporter of data and an importer of data-driven finished products and services is relevant in terms of renewed Digital Import Substitution Industrialization (DISI). The technological vision is one of seamless interactions of sensors, data analytics and representation information all housed within a single framework (Gubbi, et al., 2013). According to Boston Consulting Group: "*Connectivity and interaction among parts, machines, and humans will make production systems as much as 30 percent faster and 25 percent more efficient and elevate mass customization to a new level*" (BCG, 2015a, p. 2).

This revolution poses a policy challenge for all countries, but it is more likely to be an even bigger test for developing countries, which face additional constraints with regard to the available policy space, the level of the industrial sector's structural heterogeneity, and the initial disadvantage of being a laggard in the supply of these technologies.

In this paper, we glean indirect lessons by analogy from technology adoption and process innovation in now mature technologies to understand the key drivers of increased production efficiency in the manufacturing sector of developing countries. We first conduct a systematic review of secondary literature, and then analyse primary data for developing countries from the Innovation Surveys and the World Bank Enterprise Surveys. This is associated with a methodological caveat: can we draw lessons from previous technological revolutions? In this respect, we must remind ourselves that technological capabilities do not always or automatically turn into possibilities (Arntz et al., 2016). Technologies must be embedded into socio-economic settings, which may delay and/or limit their full deployment. The empirical strategy adopted in the remainder of this paper rests on the fact that (i) Industry 4.0 does not represent a discontinuous quantum leap from previous adoptions of digital technology, but instead entails new capabilities to support typical manufacturing functions, and (ii) the new technologies will have to run through the same process of adoption, domestication and appropriation that has characterized previous generations (waves) of technologies. These claims warrant looking at available data on past waves of digitalization to learn from the past in order to extrapolate the possible future development of Industry 4.0.

We arrive at three sets of findings. The theoretical literature suggests that the establishment of a minimum base of industrial capacity is necessary depending on developing countries specific characteristics (i.e. structural heterogeneity, lack of diversification, etc.) to enter a steady growth path. Moreover, it is important to understand that innovation performance is not only linked to structural variables, but also to process variables related to accumulated learning that allow leveraging the potential of available resources. According to the literature reviewed, a strand of studies posits and empirically tests a linear theoretical framework in which innovation inputs affect output, and innovation outputs pave the way towards successful economic performance. In these analyses, investments in R&D and human capital are generally shown to be of relevance for process innovation. Yet, another strand of literature on impacts indicates that innovation promotes company growth and increases productivity. If this is the case and since managerial decisions are purposeful, we need to align behavioural variables and expectations with the aim of improving production efficiency. The literature on specific technologies and the sparse contributions on Industry 4.0 confirm this finding by demonstrating that readiness (Luthra & Mangla, 2018) and maturity (Mittal, et al., 2018) are key variables in spurring technology adoption. Finally, our analysis of the primary data reveals that investment capabilities related to resources such as knowledge investment, human capital and information sources are important, but are likely to have a stronger effect on performance when coupled with production capabilities, i.e. process variables such as managerial experience, expectations and accumulated performance (e.g. export).

This paper proceeds as follows. Section 2 sets the stage by defining Industry 4.0 and providing an overview of the policy background. Section 3 presents the theoretical approach to innovation and technology adoption in developing countries while Section 4 reviews secondary sources on technology adoption and Industry 4.0. Section 5 presents data and the analysis's main results and Section 6 concludes.

2 Industry 4.0: definitions and policy background

2.1 Definitions

Industry 4.0 emerged as a policy concept after the term was used to denote one of the ten future projects expected to underpin the German government's approach to industrial modernization—the High Tech 2020 Strategy and subsequently the High Tech 2020 Action Plan (European-Commission, 2017a; European-Commission, 2017b). As already mentioned (López-Gómez, et al., 2017; Santiago, 2018), several terms and definitions are used interchangeably and not always consistently to refer to technologies and processes that can be broadly grouped under the label 'Industry 4.0'. There is in fact no clear-cut and uniform definition of Industry 4.0, but many ostensive definitions that simply list its technological components.

According to Hermann et al. (2015), Industry 4.0 can—from a technological perspective—rests on three pillars: a) the Internet of Things (IoT), which enables objects to interact with other smart devices and communicate with the surrounding environment; b) cyber-physical systems (CPS), which integrate computation and digital processes where embedded computers and networks monitor and control physical processes; and c) smart factories that are context-aware and assist people and machines in executing their task. According to the OECD (2017, p. 27), Industry 4.0 refers to the use of new and interconnected digital technologies in industrial production that enable new and more efficient processes across global value chains and can lead to novel products and services. The technologies listed by the OECD include: "*... developments in machine learning and data science, which permit increasingly autonomous and intelligent systems, to low-cost sensors which underpin the IoT, to new control devices that make second-generation industrial robotics possible*" (ibid). In this respect, we can also speak of Industry 4.0 as a broad umbrella term for value chain management technologies beyond firms' traditional boundaries.

Following Mayer (2018), Industry 4.0 in this paper is conceived in terms of the five technologies presented below, which cover the pre-production, production and post-production processes in different ways (see Figure 1), plotting these technologies over a classical 'smile curve' (which we will return to later when discussing the different policy concerns in developed and in developing countries).

Industrial robots. Industrial robots are automatically controlled, reprogrammable, multipurpose manipulators programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications. They largely rely on algorithms driven by software, which may be enabled to communicate with other machines through the Internet of Things and to engage in self-learning and autonomous reprogramming through artificial intelligence. Industrial robots tend to substitute routine tasks in workers' occupations.

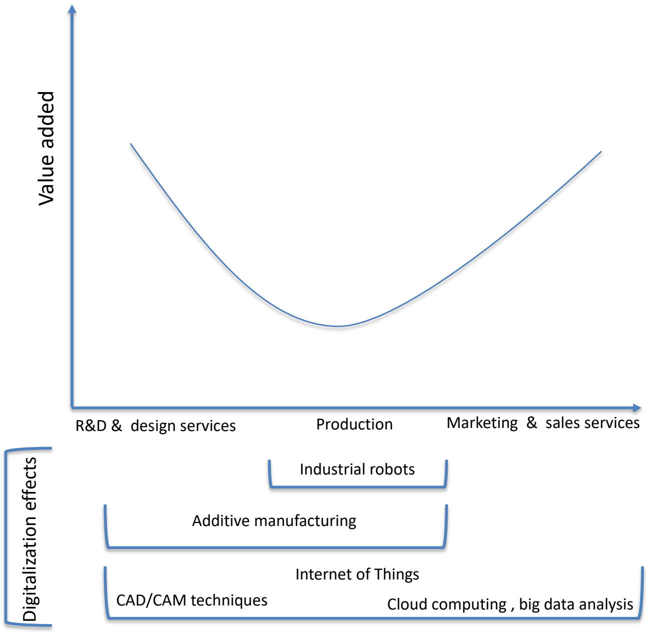
Additive manufacturing (3D printing). 3D printers build products by adding materials in layers. Using 3D modelling software (e.g. CAD), machine equipment and layering material, additive manufacturing equipment reads data from CAD files and lays down or adds layers of liquid, powder, sheet material or other materials to fabricate a 3D object. This reduces the time, material used and number of workers involved in the design, prototyping and product layout (all of which are created digitally), and facilitates product customization.

Big data and cloud computing. Big data analytics refers to a set of techniques that allows voluminous amounts of machine-readable data to be rapidly generated, accessed, processed and analysed. These processes are often undertaken through cloud computing, which substantially increases the availability and affordability of computing services by using servers, storage, databases, networking, software, analytics, etc. through the internet (i.e. the "cloud"). Machine learning systems can employ these data and recommend product features by predicting customer demand.

Computer-aided design and computer aided manufacturing (CAD/CAM) techniques. Software used to design and manufacture prototypes, finished products and production runs. CAD systems allow an engineer to view a design from any angle with the push of a button and to zoom in or out for close-ups and long-distance views. In addition, the computer keeps track of design dependencies so when the engineer changes one value, all other values that depend on it automatically change accordingly. CAD systems can first be used to build designs in blueprints, and then to create or assemble physical products and parts using computer-controlled equipment.

Artificial intelligence and machine learning. Algorithms that allow computers and machines to embody or link to computers in order to learn from data and to mimic and predict human behaviour.

Figure 1: Plotting Industry 4.0 over the Smile Curve



Source: Adapted from Mayer (2018, p. 9)

If we take a long hard look beyond the hype, however, we realize that what we call Industry 4.0 today is simply an advancement in the process of gradual but continuous adoption of electronic technologies, i.e. of ICTs (information and communication technologies) in manufacturing, which dates back to the 1960s and has accelerated since the late 1990s. In this respect, aside from the effective narrative of the four revolutions, a clear line of continuity between Industry 3.0 and Industry 4.0 is perceptible. The linear progression framework adopted by Industria2027 (the Brazilian initiative) and discussed below, for instance, breaks down production into five main functions and shows how digital technologies have progressed to support these functions across four generations, the most recent generation in a long process of technology adoption being Industry 4.0.

Figure 2: Putting Industry 4.0 into context

	SUPPLIER RELATIONS	PRODUCT DEVELOPMENT	PRODUCTION MANAGEMENT	CUSTOMER RELATIONS	BUSINESS MANAGEMENT
GENERATION 1	Manual transmission of orders	Computer-aided design system	Simple automation with unconnected machines	Manual drafting of contracts and records	Independent information systems specific by department/ area, without integration
GENERATION 2	Electronic transmission of orders	Integrated design, manufacture, and engineering calculation system	Process partially or fully automated	Automation of sales activities	Systems formed by integrated modules and databases
GENERATION 3	Computer-aided purchase, stock and payment processes	Integrated product and process data management systems	Integrated process execution system	Web-based sales support system	Web platform with databases to support operation analyzes
GENERATION 4	Real time supplier relations	Product development through product and process virtual modeling systems	Automated production management through M2M (Machine-Machine) communication solutions	Customer relations through online monitoring of products in use. Monitoring and management of customers' lifecycle	Business Management with Big Data and Artificial Intelligence support

Source: (CNI, 2018, p. 51)

Aside from its descriptive power, this framework clearly demonstrates that Industry 4.0 is not a quantum leap that has led to individual developments, but instead is the latest wave of technological advancements that—just like the previous ones—will have to be adopted and embedded into their distinct socio-economic contexts as was the case for all previous waves. This is an important point which we will return to at the end of this section.

2.2 Policies and expectations

After the launch of Germany's Industry 4.0 initiative ("Plattform Industrie 4.0"), strategic policy initiatives rapidly proliferated across Europe (European-Commission, 2017a; European-Commission, 2017b; European-Commission, 2017c; European-Commission, 2017d), in the United States (National Network for Manufacturing Innovation)[1], in Japan (Robot Strategy), in the People's Republic of China (China, 2018a; China, 2018b), and in the Republic of Korea (The Republic of Korea, 2016; The Republic of Korea, 2018). Industry 4.0 or closely related strategy and policy initiatives have also emerged in middle-income developing countries in Latin America, Asia and Africa (for further details, see Santiago (2018)). Simplifying the differences between

[1] In 2011, President Obama announced the establishment of the "Advanced Manufacturing Partnership (AMP), a national effort bringing together industry, universities, and the federal government to invest in the emerging technologies that will create high quality manufacturing jobs and enhance our global competitiveness." (https://obamawhitehouse.archives.gov/the-press-office/2011/06/24/president-obama-launches-advanced-manufacturing-partnership). AMP development was based on the recommendation of the President's Council of Advisors on Science and Technology (PCAST), which released a report entitled "Ensuring Leadership in Advanced Manufacturing."(https://obamawhitehouse.archives.gov/the-press-office/2015/11/30/ensuring-american-leadership-advanced-manufacturing).

these countries, these policy documents and action plans broadly acknowledge the significance of Industry 4.0 and aim to leverage new technological capabilities to maintain or increase their presence in global manufacturing values chains. Some countries have issued ad hoc Industry 4.0 strategic plans or included it in their overarching national plans of development (e.g. Chile's Strategic Programme Smart; in Thailand, the basic elements of the national Industry 4.0 strategy are part of the 20-Year National Strategy 2017–2036; South Africa's Industrial Policy Action Plan includes a chapter on enhancing the country's readiness for Industry 4.0). Other countries either already have an Industry 4.0 action plan in place or one that is near completion (e.g. Mexico, Viet Nam, Kazakhstan). On the other hand, there are considerable differences between middle-income developing countries in terms of their Industry 4.0 readiness level. This is evident when we look at the presence of countries such as Brazil, India, Mexico and Thailand in the global market for industrial robots compared to other middle-income developing countries (Santiago, 2018, Figure 1).

Although full digitization, virtualization and servitization of manufacturing are still at an early stage, Industry 4.0 has caught policymakers' imagination worldwide both as a source of potential gains and social risks. Digital integration and the connection of systems can create seamless digitalized value chains, thus revolutionizing the structure and governance of markets as well as the division of labour between developed and developing countries. Industry 4.0 provides a possibility to revive manufacturing and to prevent 'de-industrialization', while at the same time driving economic growth through innovation in services and merging manufacturing and services.

The potential efficiency and productivity effects of Industry 4.0 are a priority and a key objective in the policy debate, because of the well-documented relationship between innovation and long-term productivity, on the one hand, and because of the sluggish economic conditions, on the other, which have created an urgency to find new sources of growth (OECD, 2017, p. 28). Resource and time efficiency matched with productivity gains can increase industry revenues and boost global competitiveness. Real-time networking of industrial processes makes production cheaper, more sustainable and more efficient. Digital networking allows for the direct involvement of customer demands and cost-effective customization of products and services. Insights into customer behaviour have the tremendous potential of generating ideas for new products, services and solutions that could enrich people's everyday lives. This reflects efficiency in its purest form: maximum flexibility coupled with a flawless flow of value creation. Another source of potential economic gains is the full deployment of big data and data analytics. Data-driven decision-making have been found to have 5 per cent to 6 per cent higher output and productivity (Brynjolfsson, et al., 2011). Improving data quality and access by 10 per cent, i.e. presenting data more concisely and consistently across platforms and allowing them to be more easily manipulated, is associated with a 14 per cent increase in labour productivity on average (OECD, 2017, p. 30).

On the other hand, both the OECD (2017, chapters 1 and 2) and the Digital Transformation Monitor of the European Commission (European Commission, 2017a) exercise caution and moderation with respect to the current hype about Industry 4.0, underscoring the problem and barriers that SMEs and some less technologically advanced sectors of the economy, in particular, may encounter. The impact of the current digital transformation may be uneven at various levels, including for different groups of countries, within a country with social and regional disparities (Guellec & Paunov, 2017), between large companies and SMEs that may face difficulties in participating in Industry 4.0 supply chains (costs, risks, reduced flexibility and reduced strategic independence), or between different sectors of the economy. Public funding, capacity-building, enhanced planning and monitoring mechanisms, alignment of policy governance and industry co-financing need to be addressed to facilitate SME participation in Industry 4.0. In Germany, the first country to launch an Industry 4.0 policy initiative, only 4 per cent of firms in 2015 had initiated Industry 4.0-related projects and only 18 per cent of all firms reported being familiar with the concept (both data reported in Arntz et al., 2016). In Europe, only 6 per cent of ICT and professional services companies make strategic and intensive use of data, and less than 1 per cent of employed staff are data experts (EPSC, 2017, p. 4). As reported in Santiago (2018), despite the general policy interest (also in developing countries), readiness varies significantly, and adoption has thus far been very limited.

Increased efficiency and growth may come at the cost of job losses. One aspect that has attracted a lot of attention is the extent to which technologies such as AI and robotics will reduce the overall number of jobs. Current estimates are still highly ambiguous and differ widely both in academic and non-academic reports. They range from a 47 per cent loss of jobs in the U.S. to automation estimated by Frey and Osborne (2017) to only 9 per cent in OECD countries as projected by Arntz et al. (2016). The extent to which human intelligence and pattern recognition can really be substituted and embedded into machines is debatable and often overstated. As argued by Arntz et al (2016) in their evaluation of the inflated forecast of job losses due to automation predicted by Frey and Osborne (2013), experts, technology analysts and producers exaggerate the scope and speed with which Industry 4.0 technologies will actually be adopted, domesticated and appropriated in manufacturing processes. It is a fact of economic history that experts and engineers systematically overestimate the potential of new technologies (Autor, 2015; Autor, 2014).

Furthermore, cyber-physical systems (CPS) that enable geographical dispersion and fragmentation of production chains thereby facilitating mass customization, just-in-time production and optimization of inventory, may become centrally controlled by a few platforms, which may lead to increasing monopolistic or oligopolistic markets. The virtualization of supply chains and the reduction of silos is only achievable if the integrated chain (seamlessly connecting suppliers, manufacturing, logistics, warehousing and customers) is "*driven through a cloud-based command centre*" (PwC, 2018, p. 12). That is, risks exist in terms of the coordination mechanisms that will emerge to manage fully digitized and integrated value chains, who will control these mechanisms, and whether they could lead to an increasing oligopolistic and monopolistic market environment.

Other considerations are more specific to developing countries. For instance, the extent to which new technological trends might weaken industrialization in LMICs (low and middle-income countries) or provide new impetus to boost output and exports is uncertain (Hallward-Driemeier & Nayyar, 2017, p. 77). As noted by Mayer (2018, p. 3), digitalization is ambivalent as it may either bolster the reshoring of manufacturing from developing to developed countries or open new possibilities through the integration of manufacturing and services. Going back to the Smile Curve, Mayer also discusses the possibility that low value-added production activities will remain in developing countries, whereas higher value-added pre- and post-production activities will be concentrated in developed countries, a scenario that is realistic if the CPS is controlled centrally. Put differently, the advent of Industry 4.0 raises contradictory concerns between developed and developing countries with respect to the international fragmentation of manufacturing in global value chains. In the former, the primary concern currently is de-industrialization and the loss of manufacturing jobs, and Industry 4.0 may represent an opportunity to bring back production activities and boost employment. The main risk perceived in developing countries is becoming trapped in low value-added activities, and the objective is to upgrade towards higher value-added activities in R&D and design, marketing and management.

As a result, Industry 4.0 calls for coordination and integration between innovation and industrial policies in developing countries, which must also consider employment and distributional effects. Traditional technology push measures do not suffice, i.e. demand-based innovation and industrial measures will need to also take account of employability and employment, as new technologies may require the supply of complementary skills on the labour market (Acemoglu, 1998). The scope of policymaking should extend to "*supporting the scale-up of disruptive/emerging technologies, promoting commercialisation by business and adoption by SMEs, while fostering balanced regional development*" (López-Gómez et al. 2017, p. 9).

3 Theoretical background

Schumpeter describes innovation as an "engine of progress" (1976, p. 106) driving the expansion of output in the long run. This engine works through a combination of increasing production efficiency and the creation of new opportunities (new markets and new goods). Both activities lead to growth: the former through an increase in competitiveness, links to supporting activities and better use of energy and materials, and the latter through diversification, structural change and new job opportunities. In a number of previous contributions, Bogliacino and Pianta (2010) and (2013) describe these two paths as cost competitiveness and technological competitiveness, indicating that they are associated with different sources, activities and impacts.

As already mentioned, Industry 4.0 is a transformation of the production process based on the application of new technologies at the shop-floor level. In a standard demand and supply framework, the success of Industry 4.0 in developing countries hinges on demand (i.e. adoption), given that these technologies are primarily produced in developed countries according to geographical analyses on patent data (Foster, et al., 2019). In other words, to determine the likelihood that smart factories will be established, we must address the drivers of process innovation both at the firm level and in terms of contextual factors.

We thus first explain the context of the given developing country and the relationship between structural heterogeneity, circular causation and technological change. We then explore the concept of capability to better understand the micro-process of innovation, and finally, we disentangle the role of capabilities looking at its various forms.

3.1 High development theory and implications

In this subsection, we introduce the concepts of structural heterogeneity and of circular causation (*big push*). The developing country's structural heterogeneity is relevant for analysing the risks that may jeopardize the introduction of Industry 4.0 in its manufacturing sector; its circular causation, on the other hand, suggests that building a minimum industrial base is necessary to guarantee the success of an Industry 4.0 action plan. We will also demonstrate how these two factors (structural heterogeneity and circular causation) contribute to the concept of capability, which takes centre stage.

Although both structural heterogeneity and circular causation ultimately deal with the increase of GDP per capita, development and growth theory were initially two separate fields of study for an empirical and a theoretical reason. The former reason relates to the stylized fact that only a subset of poor countries accelerate their growth rate and catch up with developed countries (Acemoglu, 2009), implying that *development* is not a deterministic outcome of the club of poor countries.

The theoretical urge to develop a separate theory from the economics of growth theory is predicated on the dissatisfaction with the neoclassical theory, which, based on the assumption of marginal return to capital, suggests that capital shifts from rich to poor countries because the rate of return should be higher in poorer countries than in richer ones. Capital does not, however, simply shift from richer to poorer countries (only to a subset), and when this does occur, it does not necessarily increase productivity, suggesting that the general theory of growth needs to be further complemented.

As summarized by Ros (2000), high development theory proposes two key ideas: a) there is structural heterogeneity between a modern sector and an informal sector, with labour that is perfectly elastic at the wage rate paid in the modern sector, incorporating a premium with respect to the wage paid in the informal sector (Lewis, 1954); b) in the modern sector, horizontal externalities exist due to technological interdependencies (Rosenstein Rodan, 1943), as do pecuniary ones due to the transfer of productivity gains to both clients and providers through lower and higher prices, respectively (Scitovsky, 1954).

The growth rate increases as long as industrial sector expands, but wages do not adapt in the short run, because the unlimited supply of labour from the informal sector acts as a brake. As a result, an accelerated growth rate is not an inevitable outcome because a minimum threshold is necessary to ensure that productivity is higher than the modern sector's average wage, making investment profitable. This minimum threshold is what industrial policy needs to aim at (*big push*). Evidence that this is the case can be found in Pieper (2000).

We can derive some interesting consequences from the key assumptions of development theory: the presence of the informal sector may eliminate past productivity growth when an outflow of resources from the modern sector follows a shock; the role of interdependencies contradicts the basic tenet that international trade will cure all problems (Bhagwati, 1993) because prices do not capture all the relevant information, etc. Nevertheless, we claim that structural heterogeneity is the natural framework in which to address the issue of capabilities, i.e. the accumulated knowledge in institutions and organizations that the informal sector lacks almost by definition. In fact, the scale of development is also a measurement of the distance from the technological frontier, or to put it differently, the degree of accumulated capabilities, which explains the productivity gap and the lack of convergence, and becomes an argument in favour of industrial policies (Cimoli & Porcile, 2014; Cimoli, et al., 2006; Hausman, et al., 2007). If mastering the various functions associated with a technology requires time, then it is indisputable that a certain level of maturity is needed before a set of techniques is instituted to move closer to the technological frontier. While this could certainly hold for any economy, it is all the truer for a developing country (Lall, 1992). Lall (1992) pioneered the discussion on capabilities in developing countries, using a framework derived from evolutionary theory (Nelson & Winter, 1982). In Bogliacino and Gómez Cardona (2014), accumulated capabilities are measured as the distance from the technological frontier, estimated as TFP. Although, admittedly, a residual incorporating many different things, TFP allows for a rough estimation of efficiency and a definition of technological frontier. Since the basic unit of Bogliacino and Gómez Cardona's data is the industry-country couple, they estimate a country's frontier at industry level using the country-level variation. In their estimation, the impact of capabilities and financing constraints is of comparable size.

In a contribution using comparative data sources, Bogliacino et al. (2012) demonstrate that learning and overcoming obstacles allows building a larger knowledge base and generating a stronger innovation capacity, moving the country from technological dependency to independent technological capability. The authors identify a taxonomy of four different strategies, which are also stages of development:

- technological dependency;
- passive technological capabilities;
- integration in international technology networks;
- independent technological capabilities (Bogliacino, et al., 2012).

As a result, innovation performance generates innovation performance in a cumulative causation framework. This cumulative causation framework was recently revisited by Bogliacino and Pianta (2013). They broke down the innovation-driven engine of growth, identifying the impact of innovation performance on profits, the impact of innovation investment on innovation performance, and finally, the impact of profits on investment by softening the credit constraint. They find evidence of this virtuous cycle using industry-level data for eight European countries over the 1994-2006 period. Interestingly, when they look at microdata on Italy using a rich dataset for large companies merging innovation data with balance sheet data, they find that the very same dynamics take place within large firms at the micro level (Bogliacino, et al., 2017). Yu et al. (2017) explore these relationships using firm-level data from China, and document a profitability-growth nexus that is mediated via investment. Molina-Domene and Pietrobelli (2012) show a positive feedback loop between technological capability and export performance for three Latin American countries. Using data from Chile, Bravo-Ortega et al. (2014) analyse mutual relationships and possible feedbacks among innovation, export and productivity. They find that companies that invest in R&D are more likely to export while the reverse is not true. This is not the case for European countries, where the virtuous cycle between export and innovation is evident (Guarascio, et al., 2016), although the strength of the relationship shifts over the business cycle (Guarascio, et al., 2015). Finally, Bogliacino and Gómez Cardona (2014) present evidence that the feedback from performance to investment occurs for both profits and capabilities (measured as points of TFP distance from the leader).

3.2 Capabilities

Capabilities are executable routines or procedures that lead to repeated performance in specific contexts, i.e. they are the product of learning by an organization (Cohen, et al., 1996). Capabilities can be defined as localized learning by companies. Companies are heterogeneous, they are not the product of different initial conditions, but of local routines of search and adaptation to an uncertain environment. As discussed by Dosi and Grazzi (2010), learning entails tacit knowledge that is embedded into routines to solve problems within an organization. A technology is a recipe that requires certain ingredients as well as know-how, or the acquisition or learning of the appropriate skills (Dosi & Grazzi, 2010).

For someone to be able to make the most of an opportunity, an opportunity must first exist: the given technology should develop a product that can be used in the production process (or modified to fit in the process), and a market must be available to capitalize from the new efficiency in the production process. Behavioural factors also play a relevant role in this process: decision-makers at firm level should be able to identify possibilities to improve the firm's current situation, pay attention to technological advances, learn how to adapt existing resources to the new product, and to search the market for complementary factors that may pave the way towards new successful combinations, etc. A conventional argument posits that competition makes agents rational by correcting mistakes (Smith, 2003), but this is not necessarily the case since real markets are imperfect and behavioural biases tend to persist, given that many decisions rely on automatic processes at individual level (Kahneman, 2011) and routines at organizational level (Dosi, et al., 2005)[2].

In other words, the first set of capabilities are structural, related to enablers and resources. We label them *investment* and *technological capabilities*. This is the main contribution of a stream of literature, where innovation is treated as a production function (*Knowledge Production Function*

[2] In fact, the role of competition is far from clear. Theoretically, using an original intuition by Arrow (1962), Aghion and Howitt (1992) show that competition can be both bad and good, depending on the nature of innovation: if the latter is disruptive, the incumbent may be less likely to adopt them; if innovation is incremental, the opposite holds. Empirically, there is even less consensus: Ahmad et al. (2015) find no significant effect; Waters (2017) identifies a negative effect, and Almeida & Fernandes (2008) a positive effect.

approach). This approach pioneered by Crépon et al. (1998) breaks down the innovation process into investment in R&D, the knowledge production function and the productivity equation incorporating innovation output as an efficiency factor. The elasticity of R&D to innovation is usually positive and significant, regardless of sector and country. Information is another key factor and can be shared through markets or the institution of the research ecosystem. In other words, both demand pull and technology push factors exist (Schmookler, 1966). In the market, information is related to capabilities because of learning by doing (Verdoorn, 1993; Kaldor, 1966); whereas technology push and cooperation in research (Mowery & Rosenberg, 1979) are proxies for acquired knowledge in specific contexts based on which new technological solutions are developed along the same trajectories (Dosi, 1988).

The second set of capabilities is more process related. For the reason explained in the subsection above, variables capturing previous successes (patents, exports) are important because they depict accumulated learning. Managerial experience and behavioural intentions are also key in explaining the adoption of technology because they represent the soft skills needed to drive changes in organizations. We refer to this set of capabilities as *production capabilities.*

To sum up, two sets of capabilities are relevant for innovation and economic performance:

Investment and technological capabilities: acquired through market or other institutions, e.g. human capital, innovation expenditure, information derived from markets or other institutions of the national system of innovation;

Production capabilities**:** the product of learning within the firm, correlated with past successes (exports, past innovations), with experience and managerial skills, and with behavioural factors (intention to innovate, expectations, etc.).

This corresponds to our baseline estimation:

$$y_{ijk} = \beta_0 + \beta_0 expe_{ijk} + \beta_2 H_{ijk} + \beta_3 Info_{ijk} + \beta_4 Manag_{ijk} + \beta_5 export_{ijk} + \beta_6 Beh_{ijk} + X_{ijk}\gamma + \mu_j + \tau_k + \varepsilon_{ijk}$$

where y is the outcome variable for company *i* in sector *j* and country *k*, *expe* is expenditure, *H* is the human capital variable, *Info* is the information derived from the market or research system (the latter three are structural variables), *Manag* is managerial experience, *export* is the variable for exports, and *Beh* is a behavioural variable (these three variables are production capabilities). Finally, *X* is a vector of company level controls and $\mu_j, \tau_k, \varepsilon_{ijk}$ are unobservables at sector, country and company level, respectively.

On average, innovation correlates with size (Cohen & Levin, 1989), and size increases the importance of innovation in developing countries (Egbetokun, et al., 2016). We therefore control for size dummies. To state the obvious, correlation does not imply causation: size may be correlated with factors that are improperly measured or unobservable in the existing data source (Bottazzi, et al., 2010; Dosi, 1988), including better access to capital, more bargaining power, availability of internal resources to deal with certain constraints to enter new markets and better ability to attract managerial capital. When we are able to break down the data into sectoral taxonomies (Breschi, et al., 2000) or other groupings (Bogliacino & Pianta, 2016), the significance of size decreases or becomes much more heterogeneous. Sectoral dummies or sectoral groups capture part of this unobserved heterogeneity.

4 A synthesis of the existing empirical literature

4.1 Innovation performance: key stylized facts

Information on innovation in developing countries can basically be derived from three sources: 1) innovation surveys designed according to the Oslo Manual or equivalent (Bogliacino, et al., 2012); 2) the World Bank Enterprise Survey (which includes a follow-up survey on innovation); and 3) targeted instruments of data collection.

Innovation surveys have been used in Latin America, in particular, where a series of pilot exercises provided the foundation for standardization, culminating in the Manual de Bogotá (RiCyT, 2001). Despite being based on the Oslo Manual (OECD, 2005), it was tailored to developing countries. Data from innovation surveys are usually analysed using a model that separately considers the outcomes of the probability of conducting R&D, the amount of R&D invested, the innovation result (patent, innovation score, new product or new process) and the productivity of the company. This is known as the CDM model (the initials of the three authors) (Crépon, et al., 1998). The structure of the model is sequential: firm characteristics explain the decision to invest in innovation; conditional on the outcome of this first decision, a set of characteristics explains the amount invested in innovation; the amount invested explains the innovation score, together with other variables, and a set of inputs supplemented with the innovation score determine the company's productivity.

Most of the evidence compiled from these empirical exercises focusses on the country's investment and production capabilities, especially human capital and R&D. Aboal and Garda (2016) ran a CDM on data from Uruguay, covering the period 2004–2009, and analysed the differences between manufacturing and services. Within these broad categories, they analysed the differences between knowledge intensive business sectors (KIBS), high-tech manufacturing and other industries. The results are quite homogeneous, highlighting the role of innovation expenditure as the main driver of innovation performance. Alvarez et al. (2015) conducted a similar analysis for Chile for the period 2005–2008, examining manufacturing, services and KIBS. They also find innovation expenditure to be the main determinant of innovation performance. However, when a similar analysis for Chile for the period 1996–1999 was carried out for manufacturing only, using the share of innovation sales as an outcome variable, they find that human capital, not R&D investment, plays the main role (Benavente, 2007). De Fuentes et al. (2015) analyse data from Mexico using the same approach and compare manufacturing and services. Apart from minor differences between the sectors, R&D investment emerges as the key driver of technological innovation. For Argentina, Chudnovsky et al. (2006) determine that human capital and R&D are the main drivers of innovation performance. In Colombia, size and R&D investment drive innovation performance, regardless of industry (Gallego, et al., 2015). Crespi and Zuniga (2012) run a CDM model using data from six Latin American countries: Argentina (1998–2001), Chile (2004–05), Colombia (2003–04), Uruguay (2004–06), Panama (2006–08) and Costa Rica (2006–07). They find that firm-level determinants of innovation are quite heterogeneous when compared with OECD countries. They confirm the role of investment, whereas market and scientific sources of information have a limited impact and only in three of the six countries, which they attribute to a weak role of the national system of innovation.[3]

Another data source that is widely used is the World Bank Enterprise Survey, which has been applied homogeneously across many different countries, and includes the Innovation Follow-up Survey. The evidence from this source is more heterogeneous, because many theoretical models underpin it. Both structural and process capabilities are addressed in those contributions.

Abdu and Jibir (2018) use a sample of Kenyan firms to explore the determinants of various types of innovation using a Probit model. They find that R&D, formal training and export status drive innovation performance, while other investments in human capital do not. Almeida and Fernandes (2008) use data from the World Bank's Investment Climate Survey. They focussed in particular on the impact of technology transfer and the measure of openness and conclude that majority-owned firms have a lower propensity to innovate while this is not the case for minority-owned firms, a stylized fact that they interpret as evidence of multinational transfers of more mature technology to their affiliates. They also document an association between export and import status and higher innovation performance. The same data are used by El Elj and Abassi (2014) for four countries: Egypt, Syria, Turkey and Jordan. They arrive at some puzzling results, such as the lack

[3] The concept of the national system of innovation is the flow of knowledge and ideas among actors (both persons and institutions) of the ecosystem of science and technology within a country. The concept was introduced by Freeman and Lundvall in a number of contributions (Freeman, 1995; Lundvall, 1992).

of more innovation propensity by multinationals or the negative effect of human capital, but some results are in line with the literature, such as the role of training, ICT and size in driving innovation. Balsmeier (2017) used the World Bank Enterprise Survey to identify the net effect of unionization on R&D investment. Theoretically, union power can be both beneficial and harmful, depending on the relative strength of the two contrasting forces: unionization allows the achievement of higher cooperation with management but also induces rent extraction. According to evidence for 23 countries, the net effect is negative, especially where labour regulation is more stringent. Barasa et al. (2017) provide another relevant contribution on the role of institutions in shaping innovation behaviour based on World Bank Enterprise Survey data. They find that regional institutional quality has a significant impact on internal resources, such as R&D, human capital and managerial capability.

The Innovation Follow up Survey in Ethiopia was used by Debela Daksa et al. (2018) to study the determinants of product, process, organizational and marketing innovation. The variables human capital and size are the main predictors of all econometric specifications. Data from various African countries were used by van Uden et al. (2017) to identify the role of human capital in explaining innovation performance. The results are in line with the existing literature.

Finally, specific instruments have been designed to investigate the adoption of certain technologies or the activities of specific industries in one or more countries. This literature typically focusses more on what we have defined as process capabilities.

This is the case of the adoption of geographical information technology in Mozambique: the findings include the role of competitive pressure, donor pressure and government policy in increasing the likelihood of adoption (Amade, et al., 2018). Abu Bakar and Ahmed (2015) assess the drivers of e-marketing use among Malaysian manufacturers, concluding that objectives such as increased competitiveness and market growth (which the authors label *technology motivation*) stand out as the main predictors. Bara (2016) analyses data from case studies and secondary sources to identify the determinants of financial innovation in Zimbabwe. FDI, networks, multinational affiliation and the presence of suppliers are all relevant drivers. Luken and Van Rompaey (2008) use a dedicated survey for the introduction of cleaner technology by manufacturing firms in nine developing countries (Brazil, China, Kenya, India, Mexico, Thailand, Tunisia, Viet Nam and Zimbabwe). They find that competitive pressure and regulation play the most significant role. Bortalumy and Goswami (2015) conducted a survey among handloom manufacturers in the Assam region (India) to study the determinants of the adoption of modern technology. They find that the best predictors are ownership characteristics, using managerial capabilities, such as education and income, as a proxy. In a supplementary paper using more robust econometric techniques, they confirm the main results (Hazarika, et al., 2016). Sobanke et al. (2014) arrive at similar results for the building of technological capability among metalworking firms in Nigeria.[4] El Elj (2012) used data from a targeted survey of the Tunisian Ministry of Research to investigate technological capabilities in the industrial sector for the period 2002–2004. R&D, size and FDI are found to be statistically significant drivers of innovation, but skills are not.

Kesidou and Szirmai (2008) use data from a targeted survey for the software industry in Uruguay, and identify another important source of technology adoption: knowledge spillovers. According to their findings, local knowledge spillovers play a crucial role in explaining firms' innovation performance but not their export performance, for which international knowledge transactions play a more important role. Outside Latin America, a similar model was run in Pakistan by Wadho and Chaudhry (2018), using a specifically designed innovation survey (complying with the Oslo Manual) on textile and wearing apparel firms. The identification strategy in this case was based on a Heckman selection model. They confirm that R&D investment drives innovation performance. Market sources of information are key explanatory variables for the decision to carry out R&D. Muthinja and Chimpeta (2018) studied the adoption of financial innovation by commercial banks in Kenya, identifying the impact of technological development through a GMM-SYS estimation, and finding robust evidence. Sandee and Rietvel (2001) examined technological upgrading by rural small-scale producers in Indonesia's tiles sector, using data from a dedicated survey. Education is shown to be the most important factor, most likely capturing part of the managerial ability.

Two countries have been studied extensively, using a variety of data sources. The first case is Turkey. A survey of multinationals, conducted with CEOs, shows that R&D intensity is high in absolute terms and that technological capability is higher in MNCs than in other firms (Eryigit, et al., 2012). Another contribution used data from innovation surveys, and applied an endogenous switching regression technique: the authors find that size, foreign ownership, intangible assets and export status are key drivers of innovation, both in terms of new products and new processes (Fazlıoğlu, et al., 2018). Sag et al. (2016) document the role of network factors in the adoption of open innovation by SMEs in Turkey.

The second country that has been studied extensively is China, mostly due to its success story of rapid development. Au and Yeung (2007) conducted a survey with top managers or CEOs of industrial companies in Hong Kong SAR, China. They find that perception and behavioural

[4] The 2016 special issue of Innovation and Development on innovation in Africa shows a variety of constraints and possible solutions to contingent problems using targeted data sources (Egbetokun, et al., 2016).

variables are the main predictors of adoption. Jefferson et al. (2003), using data from a panel of large and medium sized enterprises, show that R&D performers is rapidly growing, enjoying a premium in terms of productivity. Liang (2017) uses the same panel of companies to assess the role of spillovers for technology diffusion, finding a robust effect of foreign suppliers on local companies.

4.2 What can we learn from expected impacts?

As emphasized above, behavioural factors play an important role and should therefore be considered. Since human behaviour is to a large extent purposeful, choosing whether to adopt a technology or to make the necessary investments to implement technological change, managers will be motivated by expected variations in performance. Needless to say, we cannot assume that expectations are aligned with real data, because the information set of decision-makers may differ from that available to scholars, or because of boundedly rational expectations, or because of the impact's heterogeneity, but it is important to determine a benchmark of the expected impact, estimated as an average from the existing data.

The standard approach to estimation in the literature is based on a production function framework: assuming a functional relationship between output (usually, value added or production) and input, we can augment the standard set of explicative variables using various measures of innovation performance, from having a patent to introducing a new product or process. The evidence from innovation surveys, focussed mainly on Latin American countries, indicates that innovation has a positive impact on productivity. In Chile, technological and organizational innovation have a positive impact on productivity in services, while process innovation has a significant impact in manufacturing (Alvarez, et al., 2015). However, over the period 1996–1999, there was no statistically significant effect in manufacturing (Benavente, 2007). If we consider the period 1997–2004, pooling together manufacturing and services, we find that innovators enjoyed a productivity premium (Bravo-Ortega, et al., 2014). Process innovation is found to positively have affected productivity in Argentina in the period 1992–2001 (Chudnovsky, et al., 2006), while in Mexico, between 2008 and 2009, technological and organizational innovation increased productivity in both manufacturing and services. For Colombia, Gallego et al. (2015) find an improvement in productivity following the introduction of an innovation. There is significant evidence of innovation adoption, its impact on productivity is significant in Argentina (1998–2001), Chile (2004–05), Colombia (2003–04), Uruguay (2004–06), Panama (2006–08), and Costa Rica (2006–07) using the CDM model (Crespi & Zuniga, 2012). Atalay et al. (2013) conducted a survey of top-level managers of 113 firms operating in the automotive supplier industry and find that when distinguishing between type of innovation (product, process, organizational and marketing), only process innovation significantly affects firm performance, although the outcome variable in this case is perceived performance and not labour productivity or TFP. Carvalho and Macedo's (2017) study on Brazilian firms shows that both product and process innovation have a positive impact on labour productivity, but not on TFP. Using data from innovation surveys and a framework based on Bogliacino et al. (2012), Frank et al. (2016) find that cost competitiveness (process innovation and technology acquisition) has a negative effect on output, but technology generation (product innovation) has a positive effect.

Kabulut (2015) shows that innovation in Turkish manufacturing firms positively affects a variety of measures of performance.

Change in employment level is a good proxy for company growth. When analysing the impact of innovation on employment, close attention should be paid to the distinction between innovation's direct labour saving effect, company growth through market stealing of competitors, and compensation mechanisms via price and income effects in the market (Bogliacino & Vivarelli, 2012). In developing countries, some of the compensation mechanisms work less smoothly due to lack of R&D and because of the large informal sector which constrains aggregate demand (Vivarelli, 2014). Vivarelli (2014) shows that the evidence is essentially inconclusive.

Using the approach of Harrison et al. (2014) and data from Uruguay, Aboal et al. (2015a) and (2015b) show that product innovation increases employment at company level in the manufacturing and services sectors, but that process innovation eliminates manufacturing jobs. Using a similar framework and data from Argentina, de Elejalde et al. (2015) find that product innovation positively affects employment growth and skills composition. Zuniga and Crespi (2013) use the same approach for three Latin American countries, distinguishing between different innovation strategies, and show that firms that carry out R&D (*develop* an R&D strategy) achieve higher growth than those that purchase external resources for innovation (*buy* an R&D strategy).

4.3 Advanced digital technologies: what the evidence says

What does the literature say about capabilities and the adoption of the core technologies of Industry 4.0? Since this issue is very topical (DIN/DKE, 2016; Kagerman, et al., 2013), it is difficult to find established literature on the adoption of either specific innovations or a general roadmap.[5] In fact, the literature review by Kamble et al. (2018) covering the period 2012–2017

[5] For other countries, a macro approach has been taken, with general discussions on capabilities in terms of R&D and FDI, e.g. in the case of China (Li, 2018) and Thailand (Louangrath, 2018), which have their own industrial plan (China 2025 and Thailand 4.0). In the case of Kazakhstan, the scenario is slightly different: Horvat et al. (2018) follow a similar macro approach to test the likelihood of implementation, but provide a conceptualization of the adoption process in

documents a large prevalence of contributions in engineering, mostly based on a case study approach.

Advanced manufacturing is not an alternative or a breakthrough with respect to previous trajectories of manufacturing, such as lean production, but rather a paradigm that builds upon or complements them (Buer, et al., 2018). This suggests that relying on the adoption of new processes, digital technology and ICTs can be informative for the adoption of Industry 4.0 practices.

We found at least one study on Brazilian firms that monitors the adoption of lean production technologies and Industry 4.0 technologies separately (Tortorella & Fetterman, 2018). They show that—conditional on high operative performance—there is a very high correlation between the adoption of the two sets of practices.

Another notable exception is Kamble, Gunasekaran and Sharma (2018): they study the adoption of Industry 4.0 in India through a collection of interviews with experts from industry and academia, and isolate some key barriers, such as employment disruption, high implementation cost, organizational and process change, the need for enhanced skills, the lack of a knowledge management system, the lack of a clear understanding of the benefits, the lack of standards, security and privacy issues, compatibility issues, regulatory compliance and legal uncertainty. The contribution of Luthra and Mangla (2018) on India is also noteworthy, which uses a mixed methods approach to identify challenges and barriers to adoption of new technologies in the supply chain: after applying a factor analysis, they discern four different groups of impeding factors, namely organizational challenges, legal and ethical issues, strategic challenges and technological challenges.

A similar contribution on Brazil was provided by Santos Dalenogare et al. (2018), who used a survey of 27 industrial sectors representing 2 225 companies to assess the expected benefits of technologies that lie at the core of Industry 4.0. They identified three groups of potential benefits in terms of product, operation and side benefits. They reviewed the potential links between benefits and a subset of key technologies and find that the largest number of statistically significant correlations occurs in the first group (product).

terms of different stages in an evolutionary model that is centered around the theoretical concept of Industry 4.0 readiness. For example, stage two includes the planning of automation and use of computer aided design CAD), while phase three focusses on training, automation and coordination with other companies, leaving the full digitalization strategy to stage four.

Another noteworthy contribution is Kwame Senyo et al. (2015). They focus on the adoption of cloud computing, one of the key technologies of Industry 4.0. They extracted a random sample from the list of Ghana Club 100, firms registered on the Ghana Stock Exchange, and multinational companies operating in Ghana, and conducted a questionnaire. The factors predicting adoption of cloud computing are relative advantage, security concerns, management support, technological readiness, competitive pressure and pressure from trading partners.

4.4 Summing up: evidence from secondary sources

Traditionally, the literature has adopted a resource view of the company, trying to account for innovation adoption through R&D and human capital or sources of formalized knowledge, such as the national innovation system. This is particularly evident in the literature based on innovation surveys, where the CDM model is the most widely used methodology.

These factors are important. However, they miss two key points. The very same literature reveals that innovation has a causal impact on productivity and employment growth. Unless we disregard the assumption that management decisions are purposeful, the analysis should consider that expectations drive innovation behaviour, and that managers are somehow affected by the knowledge that we have on the innovation-performance nexus.

Secondly, technology is not an input-output matrix, but rather a recipe. Consequently, specific solutions must be sought and found, responding to the heterogeneous nature of organizations. Accumulated knowledge within the organization allows making the best of resources and should be included as an explanatory factor. This is more evident in the literature on specific technologies, which is certainly more heterogeneous from a methodological point of view, but sheds light on how practical implementations require capabilities that go beyond the traditional focus on resources. For example, the literature specifically on Industry 4.0 adoption gravitates around the concepts of readiness (Luthra & Mangla, 2018) or maturity (Mittal, et al., 2018). They represent behavioural and organizational factors, triggering adoption and upgrading. Empirical evidence from Brazil and India highlights the role of expectations in driving the innovation process. This framework is similar to the theoretical background of competitiveness strategies by Frank et al. (2016), Bogliacino et al. (2012), Bogliacino and Pianta (2010).

Some underlying conclusions that can be drawn are that expectations should be streamlined on the general goals of flexibility, delivery time reduction, cost reduction, improving quality and improving productivity (Moeuf, et al., 2018), that behavioural change is important and should be explicitly addressed through non-horizontal industrial policies, and that barriers to specific resources (credit, skills formation, information flows) should be overcome.

5 Some evidence from primary data

5.1 Data sources

We use data from the Enterprise Survey by the World Bank, merged with the Innovation Follow-up Survey, launched in 2011 to study innovation and innovation-related activities. This is a firm-level survey of a representative sample of the non-agricultural formal private sector, covering small, medium and large companies.

We also use data from Innovation Surveys in Latin America. This microdata was collected either from National Statistical Offices or from government agencies in charge of conducting innovation surveys.

Details on both sources are included in Table 1 below.

To the best of our knowledge, the survey questionnaire in both sources is derived from a standard manual (Oslo Manual), with minor differences. The main advantage of the World Bank data is that they provide a code to merge the data with enterprise databases that collect additional information. The sample for the enterprise database is generally significantly smaller. Moreover—and this is a significant shortcoming—there is a major problem of missing data, which affects sample selection.

Table 1: The data sources

Source	**Managing Institution**	**Country**	**Coverage**	**Year**
Enterprise Survey with Innovation Follow-up Survey	World Bank	Bangladesh	990	2013
		DR Congo	385	2013
		Ethiopia	180	2011
		Ghana	549	2013
		India	3 492	2014
		Kenya	549	2013
		Malawi	250	2014
		Namibia	379	2014
		Nepal	471	2013
		Nigeria	905	2014
		Pakistan	696	2013
		South Sudan	543	2014
		Sudan	412	2014
		Tanzania	543	2013
		Uganda	449	2013
		Zambia	540	2013
Encuesta Nacional de Innovación de Empresas	Ministerio de Economía	Chile	5 876	2017
Encuesta de Desarrollo e Innovación Tecnológica para el sector industrial – EDIT	DANE	Colombia	7 947	2017
Encuesta de Actividades de Ciencia Tecnología e Innovación	Instituto de Estadística y Censos de Ecuador	Ecuador	6 275	2015
Encuesta Nacional de Innovación en la Industria Manufacturera 2015	INEI	Peru	1 452	2015

We provide descriptive statistics for the main variables in Table 2.

Table 2: Descriptive statistics

Name	Description	Source	Investment or Production Capability	Descriptive Statistics	Obs.
Inno Manufacturing	Adoption of any innovative methods of manufacturing products or offering services (1=adopted)	Enterprise Survey with Innovation Follow-up Survey	NA	43.30% (=1)	11 333
Inno Logistics	Adoption of any innovative logistics, delivery or distribution methods for inputs, products or services (1=adopted)	Enterprise Survey with Innovation Follow-up Survey	NA	33.41% (=1)	11 333
Inno Supporting	Adoption of any innovative support activities for processes, such as maintenance systems or operations for purchasing, accounting or computing (1 = adopted)	Enterprise Survey with Innovation Follow-up Survey	NA	33.11% (=1)	11 333
High Inno Expenditure	Dummy equal to 1 if the sum of internal and external R&D, formal training, purchase of new equipment, machinery or software, purchase or license of any patented or non-patented inventions is strictly above the country level median	Enterprise Survey with Innovation Follow-up Survey	Investment	37.10% (=1)	11 333
HK in Production	Number of skilled production workers	Enterprise Survey with Innovation Follow-up Survey	Investment	Mean 69 Min 0 Max 3 000 SD 83.68	6 518
Market source info	Dummy equal to 1 if least one client or competitor are considered to be an important source of external information	Enterprise Survey with Innovation Follow-up Survey	Investment	48.53% (=1)	11 333
Research source info	Dummy equal to 1 if the most important source of information comes from a consulting firm or a university/research institute	Enterprise Survey with Innovation Follow-up Survey	Investment	5.66% (=1)	11 333

Export share	Export/sales	Enterprise Survey with Innovation Follow-up Survey	Production	Mean 9.84 Min 0 Max 100 SD 25.76	11 333
Managerial experience	How many years of experience working in this sector does the top manager have?	Enterprise Survey with Innovation Follow-up Survey	Production	Mean 14.65 Min 0 Max 72 SD 9.77	11 333
Long-term orientation	Dummy equal to 1 if the answer to the question “What best describes the time frame of the production target?” was long term or a combination of short and long term	Enterprise Survey with Innovation Follow-up Survey	Production	60.41% (=1)	5 858
Objective	First component of a principal component analysis over the objective of carrying out innovation efforts a) to increase the quality of products or services; b) to increase the total production or amount of services offered; c) to increase the flexibility of production or offering services; d) to increase the speed of production or offering services; e) to increase the speed of delivery to the customer; f) to decrease the cost of production or offering services; g) to reduce waste or errors (defect rate or rejection rate); h) to comply with regulations or standards (e.g. safety or environmental regulations)	Enterprise Survey with Innovation Follow-up Survey	Production	Mean 0.32 Min 0 Max 1 SD 0.37	11 333
Size	Number of employees	Enterprise Survey with Innovation Follow-up Surveys	NA	Mean 37.15 Min 0 Max 10 000 SD 169.16	10 260
Process innovation	Introduced at least one process innovation	Latin American Innovation Surveys	NA	21.12% (=1)	21 550
Innovative expenditure	Innovative expenditure/sales	Latin American Innovation Surveys	Investment	Mean 0.02	21 370

				Min 0 Max 240.29 SD 1.64	
R&D employees	Employment in R&D	Latin American Innovation Surveys	Investment	Mean 1.14 Min 0 Max 778 SD 10.69	14 177
Market source info	At least one client or competitor are considered an important source of external information	Latin American Innovation Surveys	Investment	29.83% (=1)	17 980
Research source info	At least one consultant, university or public research institution are considered an important source of external information	Latin American Innovation Surveys	Investment	17.98% (=1)	17 980
Cooperation	Dummy equal to 1 if the company cooperated in innovating	Latin American Innovation Surveys	Production	24.94% (=1)	17 980
Obstacles	Predicted score from a principal component analysis of obstacle variables (internal and external financing, human capital, information, cooperation, demand uncertainty and others)	Latin American Innovation Surveys	Production	Mean 0.37 Min 0 Max 1 SD 0.41	21 550
Size	Average size	Latin American Innovation Surveys	NA	Mean 144.67 Min 0 Max 24414 SD 537.99	21 548

5.2 Adoption of new processes. Evidence from the World Bank Enterprise Survey and the World Bank Innovation Follow-up data

We use three outcome variables that capture the adoption of advanced processes and that are closer to our object of investigation. The first variable is the adoption of any innovative methods of product manufacturing or offering services; the second is the adoption of any innovative logistics, delivery or distribution methods for inputs, products or services; the third is the adoption of any innovative support activities for processes, such as maintenance systems or operations for purchasing, accounting or computing. When we use a single output variable, we take the average of the three.

Based on our theoretical framework, we use the following explanatory variables.

1. Investment capabilities:

    a. To capture investment in knowledge and innovation activities, we use the total amount spent over the three years covered by the survey on internal and external R&D, formal training, the purchase of new equipment, machinery or software, and the purchase or license of any patented or non-patented inventions. To control for different years and purchasing power differences, we build a dummy equal to 1 if the company invested more than the median;

    b. To capture human capital, we use the number of skilled production workers.

    c. We use two variables as proxies to capture the impact of the national system of innovation, the demand pull variable and the technology push variable. The latter is labelled *research source info* and is equal to 1 if the most important source of information or ideas for any innovation activity for the establishment comes from a consulting firm or a university/research institute. The former is labelled *market source info* and is equal to 1 if the most important source of information or ideas for any innovation activity for the establishment comes from recent hires from other firms, knowledge from a parent or another company, suppliers or customer feedback.

2. To capture production capabilities, we include:

    a. The share of export in total sales as a measure of past success;

    b. Managerial experience, in years;

    c. As explained in subsection 4.2, we need to control for the expected impact of the innovation. The questionnaire includes various questions related to the introduction of new processes: a) to increase the quality of products or services; b) to increase total production or the amount of services offered; c) to increase the flexibility of production or offering services; d) to increase the speed of production or offering services; e) to increase the speed of delivery to the customer; f) to decrease the cost of production or offering services; g) to reduce waste or errors (defect rate or rejection rate); and h) to comply with regulations or standards (e.g. safety or environmental regulations). Since these questions are likely to be very 'noisy' and correlated, we perform a principal component analysis to extract the latent information: we retain one component, which we standardize on the unit scale and include it as a regressor.[6] As an alternative and to check robustness, we use a dummy for a long run orientation of the planning: this is equal to 1 if the manager claims that the production targets are partially or fully oriented towards the long term.

Since the first variable in (2c) is estimated through a principal component analysis, we estimate standard errors through bootstrapping (99 replications).

To proxy for size, we include a set of dummies for small, medium and large companies (the category omitted is micro enterprises).

Finally, we partially control for potential sources of endogeneity by using both sectoral (we include four dummies for Pavitt taxonomy,[7] as in Bogliacino and Pianta, 2016) and country dummies. We cannot claim causality due to the origin of the data.

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[6] The Kaiser-Meyer-Olkin measure of sampling adequacy is 0.92 over the threshold of acceptability of 0.8. The first component has an associated eigenvalue of 5.06, whereas all others are less than 1, thus we retain only one component, which explains 63 per cent of variability.

[7] The revised Pavitt taxonomy has been proposed by Bogliacino and Pianta (2016), who also discuss its capacity to capture differences in innovation efforts, performance and overall economic performance. The taxonomy is the following, according to the international sectoral classification: science-cased (SB) are chemicals, office machinery, manufacture of radio, television and communication equipment and apparatus, manufacture of medical, precision and optical instruments, watches and clocks, communications, computer and related activities, research and development; specialized suppliers (SS) are mechanical engineering, manufacture of electrical machinery and apparatus n.e.c., manufacture of other transport equipment, real estate activities, renting of machinery and equipment, other business activities; scale and information intensive (SI) are pulp, paper and paper products, printing and publishing, mineral oil refining, coke and nuclear fuel, rubber and plastics, non-metallic mineral products, basic metals, motor vehicles, financial intermediation, except insurance and pension funding, insurance and pension funding, except compulsory social security, activities auxiliary to financial intermediation; suppliers dominated (SD) are food, drink and tobacco, textiles, clothing, leather and footwear, wood and products of wood and cork, fabricated metal products, furniture, miscellaneous manufacturing; recycling, sale, maintenance and repair of motor vehicles and motorcycles; retail sale of automotive fuel, wholesale trade and commission trade, except of motor vehicles and motorcycles, retail trade, except of motor vehicles and motorcycles; repair of personal and household goods, hotels and catering, inland transport, water transport, air transport, supporting and auxiliary transport activities; activities of travel agencies.

5.2.1 Results

We now report the results of the general regressions, pooling all countries together. Among the structural variables, innovation expenditure is an important driver of innovation, confirming the results of the existing literature. Human capital in production is correlated with at least one output variable. Information has mixed results, with demand-related information positively affecting the likelihood of innovation, while technology-related information has no significant or negative correlation.

Among investment and technological capabilities, the behavioural variable is strongly associated with innovation adoption. When we use the objective variable (Table 6), the association is stronger. We do not find any correlation with managerial experience. Exporters innovate more, at least in some of the measures.

Table 3: The impact of capabilities on adoption of new processes. Evidence from World Bank Data

	(1)	(2)	(3)
VARIABLES	Inno Methods	Inno Logistics	Inno Supporting
High inno expenditure	1.12***	0.52***	0.56***
	(0.08)	(0.07)	(0.07)
HK in production	0.00	-0.00	0.00**
	(0.00)	(0.00)	(0.00)
Market source info	0.14*	0.09	0.03
	(0.08)	(0.07)	(0.07)
Research source info	0.24	-0.05	-0.31**
	(0.17)	(0.15)	(0.16)
Behavioural (long-term planning orientation)	-0.01	0.13*	0.09
	(0.08)	(0.07)	(0.07)
Export share	0.00*	0.00	0.00***
	(0.00)	(0.00)	(0.00)
Managerial experience	0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)
Constant	0.18	0.00	-0.04
	(0.27)	(0.26)	(0.25)
Observations	3,764	3,764	3,764
Pavitt FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Size dummies	Yes	Yes	Yes

Source: 15 countries (Ethiopia excluded), manufacturing only. Logit estimation with robust standard errors. *** p<0.01, ** p<0.05, * p<0.1

Table 4: The impact of capabilities on adoption of new processes. Evidence from World Bank Data

VARIABLES	(1) Inno Methods	(2) Inno Logistics	(3) Inno Supporting
High inno expenditure	0.47***	-0.07	0.18***
	(0.09)	(0.08)	(0.07)
HK in production	0.00	-0.00	0.00*
	(0.00)	(0.00)	(0.00)
Market source info	0.01	0.07	-0.05
	(0.09)	(0.08)	(0.06)
Research source info	0.11	-0.01	-0.43***
	(0.15)	(0.17)	(0.14)
Objective	6.16***	3.38***	3.11***
	(0.17)	(0.10)	(0.11)
Export share	0.00*	0.00	0.00***
	(0.00)	(0.00)	(0.00)
Managerial experience	0.00	-0.00	-0.01***
	(0.00)	(0.00)	(0.00)
Constant	-2.73***	-1.77***	-2.02***
	(0.23)	(0.17)	(0.19)
Observations	6,159	6,159	6,159
Pavitt FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Size dummies	Yes	Yes	Yes

Source: 16 countries, Logit estimation with bootstrapped standard errors (99eps), manufacturing only. *** p<0.01, ** p<0.05, * p<0.1We also look at potential sources of heterogeneity. In Table 7, we report estimations for the full sample (manufacturing and services). The number of services firms covered is minimal, however, and the results do not change significantly. In the last three columns, we estimate the baseline model for science-based and specialized suppliers only. In advanced sectors, human capital becomes more important, as does export. The national system of innovation is less relevant (probably because knowledge is more likely to be produced internally).

Table 5: Additional results.

VARIABLES	(1) Inno Methods	(2) Inno Logistics	(3) Inno Supporting	(4) Inno Methods	(5) Inno Logistics	(6) Inno Supporting
High inno expenditure	0.48***	-0.06	0.20***	0.40***	-0.12	-0.01
	(0.09)	(0.07)	(0.07)	(0.12)	(0.10)	(0.11)
HK in production	0.00	-0.00	0.00*	0.00*	0.00	0.00*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Market source info	0.01	0.06	-0.10	0.06	0.10	-0.09
	(0.09)	(0.07)	(0.06)	(0.13)	(0.12)	(0.11)
Research source info	0.15	-0.02	-0.48***	-0.02	-0.25	-0.36
	(0.17)	(0.15)	(0.16)	(0.25)	(0.24)	(0.27)
Objective	6.16***	3.45***	3.17***	6.09***	3.37***	3.20***
	(0.17)	(0.10)	(0.09)	(0.31)	(0.16)	(0.16)
Export share	0.00**	0.00	0.00***	0.01**	0.01***	0.00*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Managerial experience	0.00	-0.01*	-0.01***	-0.01	-0.01	-0.01**
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
Constant	-2.76***	-1.78***	-1.94***	-2.94***	-1.56***	-1.74***
	(0.26)	(0.17)	(0.16)	(0.45)	(0.32)	(0.33)
Observations	6,312	6,312	6,312	2,376	2,376	2,376
Pavitt FE	Yes	Yes	Yes			
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Size Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Full sample	Yes	Yes	Yes			
Only SB and SS				Yes	Yes	Yes

Source: 16 countries, Logit estimation with bootstrapped standard errors (99 reps) *** p<0.01, ** p<0.05, * p<0.1

5.3 Process innovation: evidence from innovation surveys in Latin America

For innovation surveys in Latin America, the outcome variable used was a dummy equal to 1 if the firm introduced at least one process innovation during the reference period (the year of the survey and the two preceding years).

We could not use the same set of variables as in the other data source, but attempted to maintain the same setup, distinguishing between investment (structural) and production (process) capabilities:

1. Investment (structural) capabilities:

    a. We included the total amount spent on innovation activities in the reference period as a share of sales;

    b. To control for human capital in innovation, we included the number of persons employed in the R&D department;

    c. We used two variables to capture the impact of the national system of innovation, one to proxy for a demand pull variable and the other to proxy for a technology push variable. *Research source info* is equal to 1 if a consulting firm or university/research institute is considered an important source of information for innovation. *Market source info* is equal to 1 if clients and/or customers are considered an important source of information for innovation;

2. Production (process) capabilities:

    a. To replace managerial experience, we controlled for cooperation, and used a dummy equal to 1 if the company declared that it had cooperated in the past. We did not distinguish between types of cooperation because this was the only variable each firm was requested to provide;

    b. We could not control for export or past performance due to lack of data;

    c. Finally, controlling for a belief variable to proxy for expected impacts is also necessary. Unfortunately, we did not have variables for the objectives of the innovation activities across the entire sample of firms. The questionnaire included questions on the impact of innovation, but they were filtered: only companies with some results were asked to respond. Some questions related to perceived obstacles and were not filtered. Obstacles were "perceived" and correlated with the organization's accumulated knowledge and its internal process. This set of variables consisted of dummies, equal to 1 when an obstacle is perceived as important. The suggested obstacles are lack of internal financing, lack of external financing, lack of human capital, lack of information on the market or technology, lack of cooperation, uncertainty about demand, etc. Since these variables are likely to be noisy and correlated, we reduced them through a principal component analysis[8]. We then built a score variable and normalized it on a zero-one range.

To control for size, we introduced the same dummies as above. We included 4 Pavitt dummies to control for sector level heterogeneity, and country dummies when we pooled the data. We report Logit regressions.[9]

5.3.2 Results

In Table 6 we report the results of the regressions. We ran separate regressions for each country and a regression on pooled data; the name of the country is indicated at the top of each column.

Among the structural variables, innovation expenditure is associated with innovation performance in Peru, but not in other countries. Human capital is correlated with process innovation in the sample, but the result is not robust when we look at each country separately.

Sources of information are systematically associated with more propensity to innovate. When we look at each country separately, the general result is replicated for Chile but not for other countries.

Cooperation is important in all cases but Colombia.

Perceived obstacles are related with a higher likelihood to innovate in all countries but Colombia. The sign of the correlation may seem counterintuitive (positive instead of negative), but this variable is affected by an endogeneity problem due to the fact that innovators are also better capable of detecting obstacles.

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[8] The Kaiser-Meyer-Olkin measure of sampling adequacy is 0.93 over the threshold of acceptability of 0.8. The first component has an associated eigenvalue of 5.9, whereas all others are less than 1, thus we retain only one component, which explains 73 per cent of the variability.
[9] Although *Obstacles* is a predicted variable, bootstrapped standard errors are not well estimated with logit regressions (they routinely fail in various replications), thus we report robust standard errors.

Table 6: Determinants of process innovation for four Latin American countries

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Latin America	Chile	Colombia	Ecuador	Peru
Innovation expenditure	-0.01	-0.01***	1.28	-0.08	44.00**
	(0.01)	(0.00)	(3.35)	(0.09)	(17.56)
R&D employees	0.00*	0.00	-0.01	0.04	0.00
	(0.00)	(0.00)	(0.01)	(0.03)	(0.01)
Market source info	1.05***	2.15***	0.31	-0.31**	0.30
	(0.08)	(0.11)	(0.19)	(0.13)	(0.21)
Research source info	0.31***	1.19***	0.09	0.11	-0.17
	(0.07)	(0.16)	(0.20)	(0.09)	(0.14)
Obstacles	0.32***	0.29**	0.28	0.59***	0.52***
	(0.08)	(0.12)	(0.28)	(0.14)	(0.20)
Cooperation	0.78***	0.79***	0.12	0.63***	1.11***
	(0.08)	(0.21)	(0.20)	(0.12)	(0.17)
Constant	-2.80***	-3.27***	-14.12***	0.35	-2.71***
	(0.09)	(0.14)	(1.08)	(0.22)	(0.31)
Observations	10,554	5,835	575	2,702	1,442
Pavitt FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Size dummies	Yes	Yes	Yes	Yes	Yes

Source: Logit estimation with robust standard errors *** p<0.01, ** p<0.05, * p<0.1

5.4 Summing up

In the subsection above, we demonstrated that different capabilities are necessary to induce innovation in production efficiency, as captured by process innovation. We assert that structural variables are important, but they do not suffice: a learning process within the company is necessary to grasp the full potential of available resources.

To better depict this argument, we proceed as follows. Using World Bank data, we build a single output variable averaging out the three dummies we used previously.

We then built two index variables, one based on knowledge sources, innovation expenditure and human capital (a dummy equal to 1 if skilled employment is greater than the median); the other variable was based on export performance, managerial experience and our *Objectives* variable. We labelled the first 'Investment Capabilities', and the second 'Production Capabilities', as explained in the theoretical framework. The Investment Capabilities index is the average of the four dummies. The Production Capabilities index was built using principal component analysis over the three underlying variables and normalizing the score from zero to one.

We used a median split to define four groups:

1. Low capabilities: investment capabilities index less than 0.5, production capabilities index lower than the median;
2. Investment Capabilities only: investment capabilities index greater than 0.5, production capability index lower than the median;
3. Production Capabilities only: investment capabilities index lower than 0.5, production capabilities index greater than the median;
4. Investment and Production Capabilities: investment capabilities index greater than 0.5, production capabilities index greater than the median.[10]

In Figure 3, we report the four groups with the average outcome and confidence interval at 95 per cent.

In Figure 4, we followed a similar approach as for Figure 3, this time for Latin America. The process innovation variable was already scaled from zero to one, thus we retained it as a main outcome variable. We built two index variables, one based on knowledge sources, innovation expenditure and education; the other one based on cooperation and our obstacles variable. We

[10] Different splits provide similar results.

used principal component analysis, retained the first component for both sets and normalized them from zero to one.

We used a median split to define four groups:

1. Low capabilities: investment capabilities index less than 0.5, production capabilities index lower than the median;
2. Investment Capabilities only: investment capabilities index greater than 0.5, production capabilities index lower than the median;
3. Production Capabilities only: investment capabilities index lower than 0.5, production capabilities index greater than the median;
4. Investment and Production Capabilities: investment capabilities index greater than 0.5, production capabilities index greater than the median.

In Figure 4, we report the four groups with the average outcome and confidence interval at 95 per cent.

In both the World Bank data and the Innovation Surveys, production capabilities are associated with a larger increase in performance than investment capabilities, but the highest increase in performance is reached when the two are combined. The consistency of this result across regions is important, because we are likely to underestimate the real importance of process in Latin America because we cannot control for export performance.

In Table 7, we present the same result in a different format. We estimate OLS regressions using the group dummies as regressors, but control for Pavitt dummies, size dummies and country dummies. Based on the World Bank data, production capabilities increase the likelihood to innovate by 27 per cent versus 13 per cent for investment capabilities. The two together increase performance by 36 per cent. In Latin America, investment and production capabilities alone increase the likelihood of introducing process innovation by 2 per cent to 3 per cent, but jointly they increase it by 27 per cent.

Table 7: Structural versus process capabilities and innovation adoption

	(1)	(2)
VARIABLES	Inno Adoption Score	Process Innovation
Production capabilities only	0.29***	0.02*
	(0.01)	(0.01)
Investment capabilities only	0.15***	0.03*
	(0.03)	(0.02)
Investment and production capabilities	0.38***	0.27***
	(0.02)	(0.02)
Constant	0.32***	0.01*
	(0.02)	(0.01)
Observations	6,159	21,550
R-squared	0.29	0.15
Pavitt FE	Yes	Yes
Country FE	Yes	Yes
Size dummies	Yes	Yes

Source: Column (1) refers to WB data (manufacturing only), Column (2) to Latin American Innovation Surveys. OLS robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Figure 3: Structural and process capabilities and innovation adoption

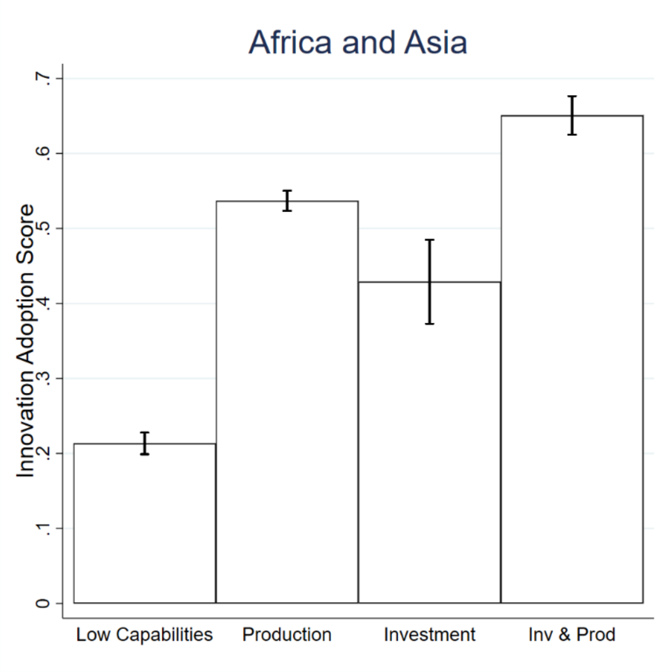
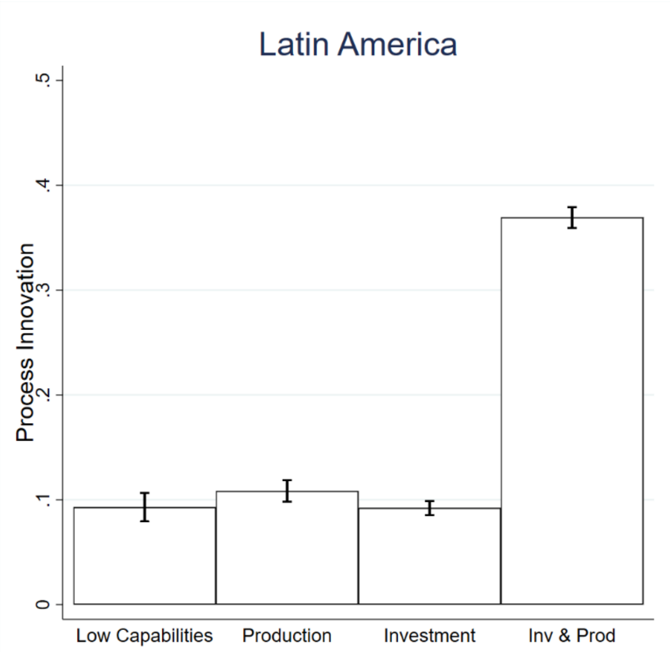


Figure 4: Structural versus process: evidence from Latin America



6 Discussion and concluding remarks

In this paper, we build on the work of Bogliacino et al. (2012) to examine how developing countries can build the necessary capabilities to upgrade their production efficiency to draw inferences from the policy mix that can pave the way towards a successful trajectory of smart factories and Industry 4.0.

We revise the existing empirical literature on the determinants of process innovation and innovation adoption. The systematic collection of innovation data using innovation surveys has been used to shed light on the main determinants of technology adoption. Investment in R&D or other knowledge capital and human capital are identified as important variables. The literature on business management has taken a different angle: it suggests companies to adapt the organization to ensure that the adoption of new technologies is not disruptive. Although data are more heterogeneous, we think that variables such as readiness and maturity are indeed important. Moreover, the expectations of impact, perception of obstacles and behavioural variables may play an important role.

We also provide empirical evidence using data from innovation surveys (in Latin America), and the World Bank Enterprise Survey (for Africa and Asia). We try to account for structural variables such as investment in R&D, human capital and sources of information, as well as for process variables such as managerial experience, expectations/perceptions and accumulated performance (export in our case).

We arrive at different findings.

- ***Innovation expenditure is a necessary but not a sufficient condition.*** Adopting new processes requires investment. Nevertheless, the adoption of technology and the introduction of new processes requires certain incentives to be aligned. The introduction of new products is more an input-output relationship, and in that case, there is probably more heterogeneity and the role of contextual factors is likely to be larger.

- ***Human capital is key, and it needs to be ready.*** Industry 4.0 is a puzzle of frontier technologies that require availability of specific skills. Both managers and employees need to understand the benefits of Industry 4.0 to promote its adoption. This necessarily implies a large investment in education and training. Employment displacement is likely to be relevant in terms of a combination of two factors: (a) automation and 3D printing will displace routine or standard tasks, and only *new tasks* are likely to be labour intensive (Acemoglu & Restrepo, 2018); (b) Industry 4.0 may potentially induce some backshoring, with some heavy consequences for global value chains and employment in developing countries. Only investment in human capital will mitigate these potential problems.

- ***National systems of innovation in developing countries must be strengthened.*** Our analysis showed mixed results in terms of the extent to which knowledge flows from research centres and market actors spur innovation efforts.

- ***Cooperation among actors of the innovation ecosystem needs to be improved.*** We found mixed results for how companies, research institutes, the government and universities collaborate to upgrade the production structure.

- ***Expectations need to be aligned.*** The review of the secondary sources and the analysis of the primary data show that behavioural variables are the cornerstone of the success of Industry 4.0 and technology upgrading. Concepts such as readiness and matureness should take centre stage in the policy mix.

- ***Cumulative causation implies that a minimum industrial capacity must be built for Industry 4.0 to succeed.*** Evidence from microdata and secondary level data suggests that a virtuous cycle exists between performance and innovation (Bogliacino & Pianta, 2013; Bogliacino, et al., 2017; Guarascio, et al., 2016; Yu, et al., 2017). The *big push* argument applies here.

When we analyse the joint contribution of investment (structural) and production (process) capabilities, we find that production capabilities are associated with a higher increase in performance than investment capabilities, but the highest production performance is achieved when the two are combined. This implies that process capabilities are necessary to grasp the full potential of new resources such as knowledge and human capital.

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