Summary Sheet

Enhancing the Quality of Industrial Policies (EQuIP) – Tool 12	
Name of the tool:	Industry 4.0 and Productivity
Objective:	Industry 4.0 is the new wave of technological change bringing hopes for accelerated industrialization in many developing countries. The ambition of catching up opportunities are accompanied by concerns about the socio-economic consequences of the adoption of new and smart technologies, including the effect they will have on the displacement of workers and potential job losses as well as the impact on developing countries' economic development trajectory. This EQuIP module seeks to provide a comprehensive set of empirical instruments that allow the investigation of the industry 4.0 uptake and potential impacts in developing countries.
Key questions:	How successful is a country in adopting new technology—in general and of Industry 4.0 in particular—in absolute and relative terms? What can be considered a reasonable target for a country to catch up, which has fallen behind in terms of adoption rate? How does a country's industrial automation capacity respond to the newly emerging technologies? How can we assess whether a country's industrial automation capacity has improved? To what extent are manufacturing jobs in the country at risk of robot-based automation? What are the productivity growth dynamics of a particular industry and what do they depend on? Are positive productivity growth rates always a good sign? Are there industries that provide positive growth and employment prospective even during the most recent periods of global market integration and fast-paced technological advancements? What is the exposure of a country to industries that have experienced positive employment, value added and productivity growth in the past? How does the share of these industries evolve over time?

Indicators used:	Share of capital goods imports Share of capital goods exports Revealed comparative advantage of capital goods imports Revealed comparative advantage of capital goods exports Share of imported 4.0 goods Share of exported 4.0 goods Revealed comparative advantage of imported 4.0 goods Revealed comparative advantage of exported 4.0 goods Import share of different 4.0 goods Robot intensity Growth rate of robot intensity Robot intensity by industry Share of employees in risk sectors Share of manufacturing employment in total employment Identification of runner industries Runner industry exposure

List of abbreviations

AD - Additive manufacturing

ADP - Advanced Digital Production

AI - Artificial Intelligence

BEC (in context with COMTRADE) - Broad Economic Categories (goods classification)

CAD - Computer-Aided Design

CAGR - Compound Annual Growth Rate

CAM - Computer-Aided Manufacturing

EQUIP - Enhancing quality of industrial policies

GDP - Gross Domestic Product

GO – Gross Output

HS – Harmonized System

IDR - Industrial Development Report

IFR - International Federation of Robotics

ILO - International Labor Organization

IoT - Internet of Things

IR - Industrial Robots

ISIC - International Standard Industrial Classification

RCA - Revealed Comparative Advantage

R&D - Research and Development

UN COMTRADE – United Nations Common format for Transient Data Exchange for power systems

VA - Value Added (nVA – nominal Value Added; rVA – real Value Added)

WDI – World Development Indicators

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1. Introduction

Many countries have high expectations of the potential of the current digital revolution and the effects it will have on the economy. The emergence of smart devices that are connected and communicate with each other are based on state-of-the-art technologies that are rapidly penetrating international markets. This is as true for the manufacturing sector as it is for the economy as a whole: sophisticated robots and powerful algorithms, which can predict when and where materials in a firm's production process need to be replaced and which react instantaneously, are increasingly performing maintenance work. At the same time, humans are increasingly assuming supervisory roles in production processes as automation technologies replace manual processes.

Serious concerns have been voiced about the socio-economic consequences of the adoption of these new and smart technologies, including the effect they will have on the displacement of workers and potential job losses as well as the impact on developing countries' economic development trajectory. The result of the reshoring of previously outsourced production processes to developing countries, for example, could potentially leave them in a position in which they are no longer able to capitalize on the same comparative advantages (low-skilled workers, which attracts production processes) of earlier industrializers. Developing countries could lose out on an essential and historically well-documented steppingstone in their path of development.

With the mandate to provide a comprehensive and accessible approach to empirical policy benchmarking for the manufacturing sector, this EQuIP moduleseeks to provide a comprehensive set of empirical instruments that allow the investigation of the industry 4.0 uptake and potential impacts in developing countries.. This intersection of technology associated with the fourth technological revolution (Anton, Silberglitt and Schneider 2001) and manufacturing is typically referred to as Industry 4.0. Even though the terms 'fourth industrial revolution' and 'industry 4.0' are often used interchangeably, it is important to define their conceptual differences at an early stage: 'Industry 4.0' identifies the intersection of the manufacturing sector with smart, digital technology. This locus is where manufacturing production machines are augmented with and implemented through modern technologies such as responsive feedback systems and sensors that are connected to a digital network that can analyse, interpret as well as adjust the production process in its entirety (Deloitte 2016).

Advanced digital production (ADP) technologies related to the fourth industrial revolution include advanced robotics, the industrial internet of things (IoT), big data analytics, artificial intelligence (AI) and additive manufacturing, among others. Applied together to manufacturing, they give rise to the concept of smart manufacturing production—also referred as smart factory or Industry 4.0. (IDR 2020)

For this EQUIP tool we identify key elements associated with industry 4.0 technologies but also measure items which do not necessarily belong to industry 4.0. These include, for example, simple(r) automations technologies as well as industrial robots. The reason for this broader focus is grounded in the observation that the technological frontier of industry 4.0 technologies is only one component of the manufacturing technology mix that is important for developing countries. As our analysis in this tool will highlight, a broader mix of production technologies appears to be linked to the successful adoption of the most advanced production technologies.

This document is structured as follows: Section 2.1 provides a general discussion of the objective and purpose of this tool by linking the emergence of new digital technology with the necessity of a multi-dimensional and manufacturing-specific analysis. It also highlights the theoretical ramifications based on a review of the recent academic and policy-relevant literature. Section 2.2

narrows down the meaning of Industry 4.0 in the context of manufacturing production processes. The different dimensions will be discussed that need to be taken into consideration when attempting to quantify *how* new and digital technologies might reshape the manufacturing industries of developing countries as we know them. The relevance of the dynamics of changes in macroeconomic variables to better understand the full scope of technological changes will also be highlighted. Section 3 introduces a specific set of empirical indicators that allow quantification of the effects of the adoption of new digital technology in manufacturing, which are subsequently applied in Section 4 in a detailed cross-country study.

1.1 Objective of this tool

1.1.1 Industry 4.0: Manufacturing in the Digital Age

1.1.1.1 Distinctive in nature, …

The fourth wave of technological innovations, characterized by the integration of digital connectivity and advanced technologies, gives rise to automated industrial systems and smart production processes that boost efficiency across economic activities. There is no doubt that this new wave of digital technology will inevitably reshape the face of the manufacturing sector as we know it. This new wave, for example, encompasses the adoption of computers and automation enhanced by smart and autonomous systems. These, in turn, are fuelled by big data and complex artificial learning algorithms while digitally connected manufacturing embraces a wide variety of technologies, ranging from 3D printing to robotics, new materials, as well as biotechnology and smart production systems.

It should become clear from this very broad definition that the effect of this new wave of digital technology will reach well beyond the manufacturing sector and will also leave its marks on the service sector and the consumer market: *IoT products*[1], such as autonomous cleaning robots or smart controls that make it possible to remotely control and adjust the room temperature of a house while being hundreds of kilometres away, have recently found their way out of *sci-fi* movies and into the lives of regular consumers. This tool does not seek to analyse the effects these incredible technologies may bring with them. Instead, our analysis focuses on the *production-related* dimension of manufacturing technologies. This distinction is important as the most recent digitalization of the manufacturing production process also allows for the creation and distribution of different forms of *intangible assets* which are also of high relevance for the manufacturing industry: these include digital blueprints of production, different types of software, algorithms or, more generally, patents, all of which complement the new and digital production cycle. This *intangible dimension* of the modern production process is a highly complex as well as regionally concentrated phenomenon and researchers have only identified a countable number of regions, countries and institutions that are involved in this part of the modern economic process. While a selective summary of the trends and directions this development has taken is provided in **BOX 1.1**, the main focus of this tool is on the *tangible dimension* of the manufacturing production process. The reason for this is two-fold:

First of all, many highly recognized international organizations have sought to analyse the effect of *intangibles* in this equation. This requires very detailed and specific information on firms and products (see **BOX 1.2**). Such an analysis is granular by its very own definition and makes it fairly difficult to arrive at a comprehensive and comparable stratum of results across industries and countries. Such a micro-founded analysis may leave some important aspects relating to policy evaluation unanswered, particularly for the developing world.

The purpose of this tool, therefore, differs slightly: its goal is to provide policymakers *across the developing world* with tools to identify changes in the adoption behaviour of new digital technologies **and** to link such behaviour to macroeconomic outcome variables that are of crucial importance to policymakers: value added and employment. Consequently, the instruments proposed in this tool place special emphasis on the introduction of summary statistics that can be applied across a *broad group of countries and manufacturing industries* while retaining a high degree of space for interpretation and benchmarking. It goes without saying that this tool should therefore be seen as complementing analyses of digital dispersion within manufacturing industries instead of competing with them. An in-depth analysis of this fundamental question requires both a highly granular and a micro firm-level data specific analysis together with a more macro- and cross-country-oriented perspective on the effects of the adoption of digital technologies.

1.1.1.2 … yet part of a long history of technological change

At the same time, this tool highlights the importance of not only looking *across countries and industries*, but to bear in mind the *time dimension* of manufacturing development as well. The term *Industry 4.0* clearly refers to the long history of technological change (three waves): beginning in the late 18th century with the advent of steam power and the invention of the power loom, the *first industrial revolution* ushered in mechanization and radically changed how goods were manufactured. In the late 19th century, electricity and assembly lines made mass production possible, giving rise to the *second revolution*. Many cite the *third industrial revolution* as beginning in the 1970s, when advances in computing introduced pre-programmed machines and networks, thereby expanding automation. To that end, the *fourth technological revolution* signifies the current end point of technological evolution, which allows us to connect machines and harvest their efficiency through coordination, automated problem solving and the utilisation of new materials and production technologies.

It goes without saying that all technologies associated with their respective revolutionary waves were considered to be inherently destructive: the introduction of assembly lines, for example, not only revolutionized the automotive industries, but also posed a great challenge for workers. The same is true for the textile and garment industry and/or the emergence of IT systems in the past. It is therefore important to recognize that new technological discoveries posed threats as well as opportunities for society and companies in the past as well, and that it should not come as a surprise that it is no different in the case of the most recent digital wave: a recent study (Frey and Osborne 2017) estimates that up to 47 per cent of jobs have been identified as being 'at risk of computerization.'[2] Similar predictions have been made by, among others, Harari (2018), who argues that past technological waves shifted human activity from physical to cognitive activity. The result of this current wave may very well be that machines will start taking on many of the cognitive tasks, leaving very little space for humans who only have the capacity to carry out physical and cognitive activities.

While it is certainly true that the degree between digital/automated and human skills has certainly increased with the emergence of ever smarter and more sophisticated digital technologies, the consequences of this development are difficult to quantify and their scope and magnitude remain almost impossible to predict: looking at job-related tasks rather than the individual jobs themselves, Arntz, Gregory and Zierahn (2016) find a much lower risk of computerization than Frey and Osborne (2017), who use an occupation-based approach, although they also find that certain jobs and industries are more at risk of job losses as a result of computerization. Consequently, workers, industries and countries with a given sectoral composition of the economy and labour force may face very heterogeneous risks and threats. This is an important point as new digital technologies will not only pose tremendous challenges in the future, they will also create winners and losers and may potentially result in increased inequality, calling for strong policy interventions. Autor et al.

(2018) quantified the negative socio-economic effect of the disappearance of manufacturing jobs for young American men due to the increase of global manufacturing competition. It is not unlikely that similar tendencies may be observed in the developing world in the future as a result of the adoption of new technologies.

It is therefore of utmost importance for policymakers to be aware of both the opportunities as well as the threats of the adoption of new digital technologies for the economy in general and the manufacturing sector in particular: where new production technologies will generate unprecedented growth in some industries, they will stifle others. Old jobs will disappear and new, more high-skilled ones will emerge. Consequently, finding a suitable framework and incentive structure that fosters the formation of appropriate capabilities to create modern industries and achieve successful job transition through skills upgrading while fighting inequality and other negative side effects will be the major challenge for policymakers in the future. This EQuIP tool aims to provide a set of useful indicators to help policymakers successfully navigate these challenges.

1.1.2 Beating the buzzer of technology adoption: Sluggish despite its high policy relevance

1.1.2.1 The slow uptake of Industry 4.0 technologies in developing countries …

Each industrial revolution marks a major turning point in the shift of technological, socioeconomic and cultural conditions. Waves of technological change and paradigm shifts, driven by the surge of scientific discoveries, have followed one another in accelerated succession. Because accumulated technological and productive capabilities of countries differ, a 'role model' of successful adoption that would suit all countries does not exist; nor is there a one-size-fits-all policy solution to respond to challenges and opportunities (Lacasa et al. 2019; Lee and Malerba 2017).

The expectation of what the new wave of technological innovation could potentially bring to the table for the developing as well as for developed countries is twofold: for developed countries, Industry 4.0 could present an opportunity to regain manufacturing competitiveness. For developing countries, Industry 4.0 could provide a means to moving up the value chain, an increasingly important goal in the face of rising labour costs.[3] On the other hand, Industry 4.0 could also lead to a further and more rapid reduction of manufacturing jobs in the developed world (Frey and Osborne 2017), while countries excluded from the 4th industrial revolution (e.g. least developed countries) could be affected by the uptake of manufacturing jobs by other countries (e.g. developed countries that can more easily embrace new technologies and thus compete with the poorest countries). In other words, the comparative advantage in terms of abundant and cheap low-skilled labour may be offset by the adoption of these new technologies in the developed world. Policymakers are likely to adopt Industry 4.0 technologies in order to 'jump on the bandwagon' of the unfolding industrial revolution in the hopes of either boosting their country's economic performance (productivity), or because they fear that their country will otherwise fall behind in the adoption of new technologies. The creation and diffusion of new digital technologies has thus far been quite limited: less than ten countries hold 85 per cent of all triadic patents[4] for emerging technologies such as computer-aided design and computer-aided manufacturing (CAD-CAM), robotics or additive manufacturing, while 77 per cent of all exports are directly associated with these technologies (see Appendix A). At the same time, 84 countries remain excluded from the global creation and use of such technologies (Foster-McGregor, Nomaler and Verspagen 2019; UNIDO 2020).

In the same vein and from a policy strategy perspective, Santiago (2019) finds that the majority of highly industrialized countries have already paved the way to accelerate their economic transformation to embrace Industry 4.0, while developing countries seem to be lagging behind. According to Santiago, at least nine industrializing countries have announced national strategies on advanced manufacturing, reflecting a diversity of approaches, including industrial policies or science, technology and innovation plans and standalone feasibility studies. A number of middle-income economies, such as the BRICS, have already adopted smart manufacturing and are even entering areas traditionally reserved for highly industrialized countries (Daudt and Willcox 2016; López-Gómez et al. 2017). China, for instance, is adopting industrial development strategies that seek to capitalize on new windows of opportunity to benefit from its increasing ability to produce new technologies: its search for value addition and enhanced technological content is superseding traditional cost advantage strategies (Lee 2019). Apart from large developing countries, only a handful of smaller countries have defined or are in the process of developing strategic policy agendas around smart manufacturing; this is rarely observed for the group of least developed economies.

1.1.2.2 … and the significance of capabilities

The willingness—and perhaps even more importantly the **readiness** of a country to adopt new technologies—requires a minimum foundation of industrial capabilities. In UNIDO (2020), a clearly positive relationship is established between the adoption of new technologies across different countries; both in terms of innovators and producers as well as, more generally, of the utilization of technologies associated with the 4th industrial revolution and their average set of industrial capabilities. Similarly, Andreoni and Anzolin (2019) identify five categories that differentiate developed from developing countries as regards their Industry 4.0 readiness: 1) basic capabilities, 2) retrofitting and integration, 3) digital infrastructure, 4) digital capability gap, and 5) access and affordability.

The development of appropriate capabilities and meeting the abovementioned prerequisites represent an essential building block in the successful adoption of new digital technologies. At the same time, the development of such ‘enablers of development’ goes far beyond the immediate concept of digital technology adoption within manufacturing. In fact, these enablers are crucial for the successful development of a country as a whole. The EQuIP toolbox has long recognized the integral importance of developing such capabilities and meeting the prerequisites, and on this premise created the **EQuIP TOOL 9: Industrial Capabilities Indicators**[5]. The tool identifies a country’s industrial capabilities to better understand the role these play in industrial production and technological and structural change: a country’s industrial capabilities are reflected in firms’ competencies (production and its organization, technological changes and innovations, etc.) as well as firms’ production capacity (investments in machines, equipment and other capital goods, etc.). A country’s industrial capabilities are also reflected in the physical and institutional infrastructure supporting the productive economy. This is why countries’ industrial capabilities are the main ‘drivers’ and ‘enablers’ of countries’ industrial competitiveness.

The interested reader is kindly referred to this particular tool for a more insightful and detailed discussion on the issues addressed above. A further discussion on the role a country’s capabilities plays in the wake of the emergence of new digital technologies in developing countries with a focus on firm-level evidence is provided in UNIDO (2020).

1.1.3 Learning through adoption: Trade as the key channel of Industry 4.0 technology adoption

The adoption and diffusion of technology across the economy are fundamental steps if a country is to capitalize on the window of opportunity of Industry 4.0. The experiences of some of the most successful manufacturing firms in East Asia suggest that learning is not possible without technology adoption. Most of the successful firms in the region began adopting foreign technologies for production processes first, resulting in knowledge transfer and ultimately mastering these technologies and enhancing productivity (Lee 2019). The Republic of Korea and Taiwan, for instance, followed in the footsteps of an early industrializer, Japan. Similar episodes of imitate-to-innovate have also fuelled the successful emulation of new production processes and products in China.

From latecomers to followers, benchmarking adoption is crucial. One of the key concerns of today's latecomers is whether they have invested enough resources at the national level as part of their adoption process of new technology to turn into a successful follower and if not, how far they have fallen behind. An important insight from the historical perspective is that latecomers do not necessarily have to become original inventors of new technologies themselves. Rather, taking small, well-informed steps to test technology and policy options in relation to the goals being pursued, has proven to be the preferred strategy before fully committing to the implementation of the present policy tool. Building on this rationale, the main starting point for the successful adoption of Industry 4.0 technologies in developing countries could either be a fast-paced adoption process of the emerging technologies or a more adaptive response to the local circumstances through incremental, follow-on innovations. In either case, imports of Industry 4.0 goods[6] may be an indicator of the adoption of technological change in developing countries.

Contribution 1: The adoption of new technologies

This tool provides a simple set of measures to quantify the adoption of new technologies linked to Industry 4.0 in different countries. It introduces a methodology that allows measuring, quantifying and categorizing differences in technology adoption and diffusion strategies across economies through the trade structure of Industry 4.0 goods.

1.1.4 The impact of Industry 4.0 on employment: different mechanisms at play, uncertain outcome

"The difference between human labour and horses is that humans have a comparative advantage in new and more complex tasks. Horses did not." (Leontief 1958). While this statement most certainly applied in the past, it is now being argued (e.g. Harari (2018)) that while past waves of technological revolutions shifted human activity from physical to cognitive activity, the result of the current technological wave may very well be that machines will start taking on cognitive tasks. This may lead to a higher degree of competition between humans and machines and leaves less overall space for humans, who only have the capacity to carry out physical and cognitive activities. In other words, automation is replacing repetitive tasks and new more complex tasks are being created. At the same time, smart technologies may also 'eat up' parts of the cake. Will there be room for future employment despite these trends?

The labour force in most economies are no longer dominated by an undifferentiated mass of unskilled workers but are characterized by workers with a dynamic skills portfolio. Tasks that were previously carried out manually have now been automated, while at the same time, other new technologies complement labour (known as the 'labour augmenting effect'). Consequently, automation is typically counterbalanced by the creation of new complex tasks in which labour has a comparative advantage, and even more so if skill-enabling technology is introduced. Such new tasks do not only have a positive productivity effect, they also have a reinstatement effect, i.e. they reinstate labour into a broader range of tasks through re-skilling and up-skilling. Automation replaces low-skilled human labour, namely workers who engage in routine and repetitive tasks, while the emergence of new tasks tend to benefit skilled workers. This process increases social inequality in the short run, but the standardization of new tasks over time tends to help low-skilled workers take on more complex tasks. Both automation and the creation of new tasks increase inequality in the short term, but also establishes conditions under which stability and equality can be achieved in the long run. These effects have been extensively discussed in the automation literature (see, for example, Acemoglu and Restrepo (2017), Acemoglu and Restrepo (2018), Acemoglu and Restrepo (2019) or Aghion, Jones, and Jones (2017)).

In a recent study, Frey and Osborne (2017) examine the expected impacts of future computerization on US labour market outcomes and conclude that around 47 per cent of total US employment is at risk of computerization. The study also finds that wages and educational attainment exhibit a strong negative relationship with an occupation's probability of computerization. In other words, it is especially the less educated and less qualified working class population that will be most affected by the emergence of smart digital technology. While it is certainly true that the emergence of even smarter and more sophisticated digital technologies has increased the degree of substitution between human and digital labour (Frey and Osborne 2017; Harari 2018), the consequences of this development are difficult to quantify and their scope and magnitude remain almost impossible to predict: looking at job-related tasks rather than at the jobs themselves, Arntz, Gregory and Zierahn (2016) find a much lower risk of computerization than Frey and Osborne (2017), who take an occupation-based approach, while they also find that certain jobs and industries are more at risk of job losses as a result of automation. Consequently, workers, industries and countries with a given sectoral composition of the economy and labour force may face very heterogeneous risks and threats. This important insight has also been confirmed by Nedelkoska and Quintini (2018).

Although the impact on jobs remains uncertain, two observations are for the most part indisputable:

- The job and skills requirements associated with the fourth industrial revolution highlight human capital as a key enabler for industrial development. Insufficient exposure to high-technology jobs may hamper the ability to adapt and properly respond to the disruptive changes expected from Industry 4.0 (IDR 2020; Leopold, Ratcheva and Zahidi 2017).
- Secondly, heterogeneous employment effects across types of jobs and industries are expected across the globe (Arntz, Gregory and Zierahn 2016; Frey and Osborne 2017; Nedelkoska and Quintini 2018).

Because manufacturing industries are characterized by unique structures of labour-capital composition, it is likely that the impact of automation on manufacturing will differ across industries. Moreover, the productivity effects of different technologies vary significantly, i.e. one set of automation technologies will not affect labour demand in the same way as others. In fact, there are multiple industries that benefit from productivity dividends while generating employment at the same time; either because new production processes require manual inputs at different stages of the production process (Autor 2015) or because only specific tasks have been 'rationalized away' (Arntz, Gregory and Zierahn 2016).[7]

It should be clear from the above discussion that the threat of automatization is closely linked with country-specific characteristics and the configuration of the country's manufacturing sector: if those industries that will be strongly affected by digital technologies do not play an essential role in the country's manufacturing sector, concerns about computerization-induced unemployment will likely be relatively low. On the other hand, if those industries are drivers in the country's manufacturing sector, computerization will likely be of high relevance and must therefore be closely monitored. To quantify the risk of job losses due to automation, the scope of the analysis needs to be narrowed down and precisely defined: the focus will therefore be on the type of computerization that is most obviously connected to the potential loss of existing jobs in the developing world. In the context of manufacturing, the threat to employment is that as creative destruction unfolds, the destructive part is expected to fall primarily on industries with robotic automation (Mayer 2018). This is a highly dynamic area as rapid technological changes have halved the price of industrial robots between 1990 and 2005 (Graetz and Michaels 2018), which means that industrial robots are closer to becoming a cost-efficient substitute for human labour than ever before.[8]

Contribution 2: Robots and job losses in manufacturing

The second contribution of this tool is that it provides a set of instruments that allows policymakers to identify and quantify the (potential) risk of job losses associated with the emergence and adoption of robotic automation. It proposes a comprehensive set of indicators to carry out country- and industry-specific benchmarking exercises across countries.

1.1.5 The view ahead: What to expect from Industry 4.0 in the medium and long run?

One economic principle is that any kind of technological innovation will only gain a foothold if it is beneficial for the firm to adopt the new technologies. In other words, only if the newly available technologies result in an improvement of the production processes by increasing their productivity will they be integrated in the production processes of the economy. This principle is as true for any previously adopted technology as it is in the context of the current wave of technological advancements: when countries plan their strategies for Industry 4.0, their expectation is an increase in productivity of their economy's production process while ideally preserving if not increasing jobs through the opening of new markets.

The traditional neoclassical growth accounting method is typically used in the literature to estimate the contributions of technological change and capital upgrading to output growth. Productivity gains in terms of production factors usually derive from (a) a process of capital deepening, i.e. a more extensive use of machinery relative to manual labour; and (b) an increase in productivity (defined as the ratio of value added created per employee in the production process). In most developing countries, the improvement in productivity is a result of the growth in capital stock, i.e. more machines replacing the mass of low-skilled workers. On the other hand, increases in total factor productivity, i.e. an increase in technology use as a result of implementation of new technologies, is more apparent in developed countries. Without further decomposition, the expected impacts on productivity may vary from the effect of capital deepening as opposed to the increase in capital per worker to the effect of pure technology growth. In this sense, productivity is an imperfect proxy of the impact of technological change, yet an analysis of productivity allows us to derive important insights as far as the dynamics of production processes is concerned.

The reason this tool places such emphasis on the role of productivity as opposed to capital deepening is threefold: first of all, productivity allows us to capture the 'learning effect' associated with the adoption of new technologies, e.g. through more efficient handling of machinery. Secondly, obtaining a concise measurement of capital stocks across industries is an advanced and relatively technical exercise, which is probably more suited for a more academic discussion and would certainly miss the scope and objective of EQuIP. Lastly, and most importantly, the concept of productivity is closely linked to two variables of high policy relevance: an industry's measure of performance (value added) and inclusion (employment). It lies at the core of this tool's second tier (technology absorption and productivity) to provide guidance on how productivity growth can be reconciled with the objective of increasing performance and reciprocity.[9]

The central question linking the concept of Industry 4.0 adoption and productivity growth are the following:

- What can be learnt from past waves of technological change?
- Can past technological change predict the level of Industry 4.0 adoption?

On the one hand, the adoption of Industry 4.0 technologies can be monitored year over year through appropriate indicators. Preparedness for the possible impacts of Industry 4.0 adoption on productivity and employment in different industries is a key element in elaborating possible responses to the adoption of Industry 4.0. No one can anticipate what the consequences of the adoption of Industry 4.0 technology will be; however, we can at least get an idea by analysing data from past waves of technological change. This is because previous waves of technological innovations have been observed through the same productivity transmission channels as the current Industry 4.0 wave; their adoption rate has also been determined by the degree to which they have facilitated an improvement in industries' production capacity. Based on these insights, the following propositions can be made:

Technological change did not penetrate all countries to the same extent. The impact of the current wave of technological innovation will vary greatly across industries: even though Industry 4.0 will affect all countries and industries, the degree will differ substantially. There is, however, no reason to believe that Industry 4.0 will only affect high-income countries or particular industries only. Technological change also did not penetrate all industrial sectors to the same extent. As has been the case in all previous waves of industrialization, different countries adopt different strategies at different periods of time – not because they were necessarily 'too late' but rather because their industrial composition demands a different policy approach than that of other countries. Technological change is not always reflected in a simultaneous increase of manufacturing value added, productivity and employment, but often generates trade-offs. Some industries might have retained a productivity profile that is highly favourable for the country's economic development. This does not, however, imply that the same approach would be successful in any other country.

Contribution 3: The interplay between technological change and productivity growth

The third contribution of this tool is linking the current debate on the technological revolution based on the emergence of smart digital technology to macroeconomic indicators across manufacturing industries. The instruments presented in this tool allow for a simple analysis of the differences in the dynamics of manufacturing industries' productivity, value added and employment growth over time. It also proposes a simple method to analyse and compare country-specific industry profiles across aggregates over time and furthermore defines a simple forward-looking tool to identify the direction in which a given manufacturing industry is developing.

1.2 The structure and concept of this tool

1.2.1 Introduction

Many countries have high expectations of the potential of the current wave of digital technology and the effects it will have on the economy. International organizations such as the World Bank, OECD as well as UNIDO have devoted a large part of their resources to providing a better understanding of how these new technologies may reshape our economies (see Box 1.2 for more information).

Box 1.1: Intangibles vs. tangibles in the domain of new digital technologies and Industry 4.0

A lot of research Is available on the dimension of intangible technologies introduced by the current wave of technological advancements. Vincent, Vertesy and Damioli (2019) report a huge increase in artificial intelligence (AI) patenting activities since 2013 with a significant boom in 2015-2016. They also observe a very high concentration of AI intellectual properties in a few countries. Moreover, the majority of AI patenting activities remain concentrated in specific sectors including software programming as well as high-technology sectors such as medicine, aeronautics, electronic equipment and machinery as well as vehicles, but AI patents seem to be rapidly growing in traditionally less technology-intensive industries as well, such as food and beverages and agriculture.

This EQuIP module takes a close look at the *effects of Industry 4.0 and the adoption of new technologies on the manufacturing sector*. Even though this only allows us to address some of the effects of the adoption of new digital technologies, we closely focus on **manufacturing industries and developing countries** in particular. This distinguishes our study from others that have been carried out on this topic. It is important to point out that our analysis complements other research findings rather than representing a holistic analysis on new technologies.

Box 1.2: Micro-level evidence on the effect of Industry 4.0 in advanced economies

Whereas this EQuIP module takes a cross-country and manufacturing industry-specific focus, other studies have taken a more granular look at the effect of digitalization on productivity:

Andrews, Nicoletti and Timiliotis (2018), for example, identify drivers of digital adoption for European countries while Gal et al. (2019) study the potential of digital technology for productivity growth. Both studies use firm-level data to explore firm-level characteristics and the gap between different firms at the technological frontier based on their use of digital technologies such as access to high-speed internet, simple and complex cloud computing as well as back and front office integration systems.

The two studies find that capabilities such as managerial and technical skills as well as business-related incentives such as the business environment in terms of competition are the drivers of technology adoption at the firm level. In essence, both studies conclude with the following policy suggestions:

- Skills must be upgraded by enhancing initial education and training systems as they are prerequisites for the adoption of digital technology;
- Infrastructure, such as access to broadband internet, must be improved;
- Barriers to starting a business must be lowered;
- New competition policy for platform firms must be introduced;
- Financial constraints, especially for young firms, must be lowered and tax systems updated;
- Lastly, usually only a small fraction of firms at the technological frontier are the ones to adopt new technologies fastest. Digital adoption seems to be a strong indicator for productivity gains.

When considering the effects of technological revolutions on manufacturing processes, it is important to understand that technological evolution is not a one-way street; it is instead an important and interconnected component of a modern economy. Figure 1.1 illustrates this point: new technologies (such as Industry 4.0) will only be adopted into the production processes of an economy, if there is something to be gained from doing so. These potential gains could be manifold[10], but typically also affect a production process' efficiency: if a new technology allows a firm to produce more output with the same amount of input, it will be keen to adopt this technology. If this technology is adopted by many/all firms of the country, their productivity gains reach macroeconomic dimensions, and macroeconomic indicators will reflect the changes in the production dynamics which result from the newly adopted technology.[11]

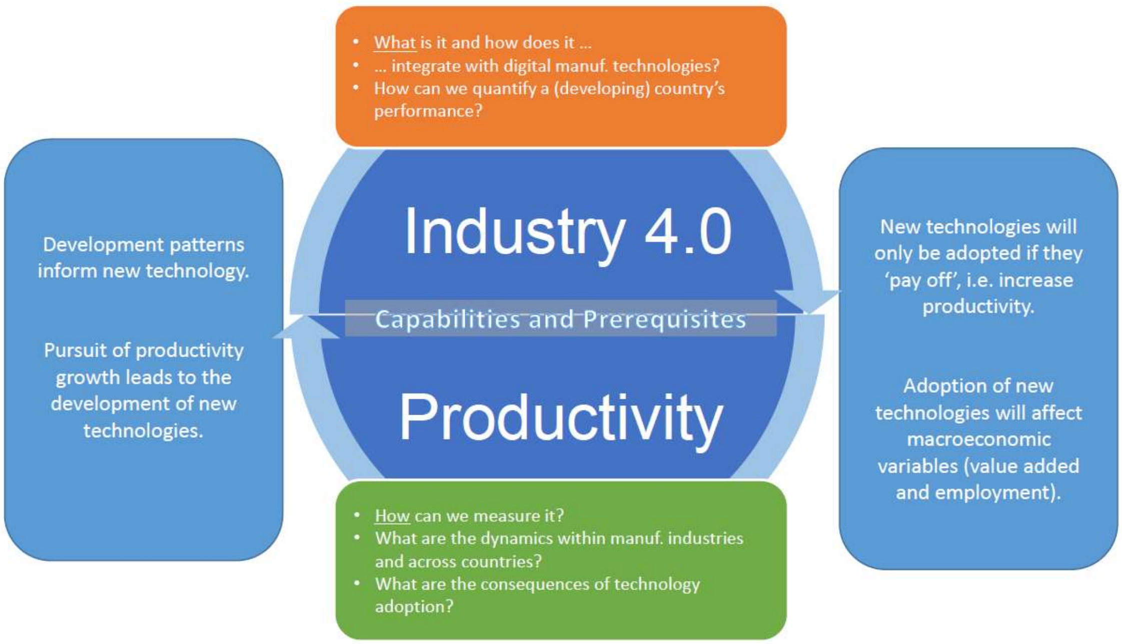


Figure 1.1: The interplay between new technologies (Industry 4.0), capabilities and productivity

New technology rarely appears out of nowhere, however. Research and development (R&D) expenditure is a major indicator of a company's success: if a company conducts an evaluation of how new technologies could improve its production processes, it will not only set the company apart from competitors that are less involved in R&D activities, but will also result in the creation of new technology. That is, the pursuit of productivity growth also leads to the development of new technologies. The dimensions of 'adoption of new technologies' and 'productivity' are two sides of the same coin and should always be considered together. This point is important as new digital technologies will not only be restricted to a few sectors or industries but will affect the entire economy (see **Box 1.3** for more details).

Box 1.3: Digital technology industry classification

Calvino et al. (2018) propose a taxonomy of sectors based on the extent to which these have gone digital. They build their indicator on a battery of measures of digital complexity such as the share of ICT tangible and intangible investments as well as purchases of intermediates, share of specialized personnel or the stock of robots.

While they find that some sectors such as telecom and IT services are consistently positioned at the top of the distribution of sectors in terms of adoption of new digital technologies, other industries vary more strongly across the proposed dimensions of the indicator. Within the manufacturing sector, the authors identify electrical equipment, machinery as well as transport equipment and electronics to be the most digitally intensive industries.

At the same time, it goes without saying that the relationship between the adoption of new technologies and productivity growth is very complex. As illustrated in Figure 1.1, what glues these two domains together are the necessary **capabilities and preconditions** enabling successful communication between these two domains. Because of the significance of this component, **EQuIP TOOL 9: Industrial Capabilities Indicators** aims to shed light on all of the relevant dimensions needed to provide the proper starting conditions for robust economic growth within—but not exclusive to—manufacturing.

The remainder of this section presents a conceptual framework on **the definition of Industry 4.0** and how it is integrated with digital manufacturing technologies, focusing in particular on developing countries. We then discuss how to measure and identify different kinds of productivity growth dynamics.

1.2.2 Adoption of new technologies in manufacturing

Within the policy debate, many countries are directing their industrial strategies and policies towards the adoption of technologies associated with the fourth wave of industrial innovation in the hopes that new technologies will boost economic performance through increased productivity and by opening new markets. What does this wave of new digital technology in manufacturing actually entail and how could it affect developing economies? To answer this, we must define some concepts first.

This section aims to identify how new digital technologies enter the domain of manufacturing: they enter at the intersection where the latest digital and production technologies and manufacturing production processes meet. This domain is referred to as the **smart factory**, which is populated by a very specific set of production technologies and concepts (see Figure 1.2 for more information).

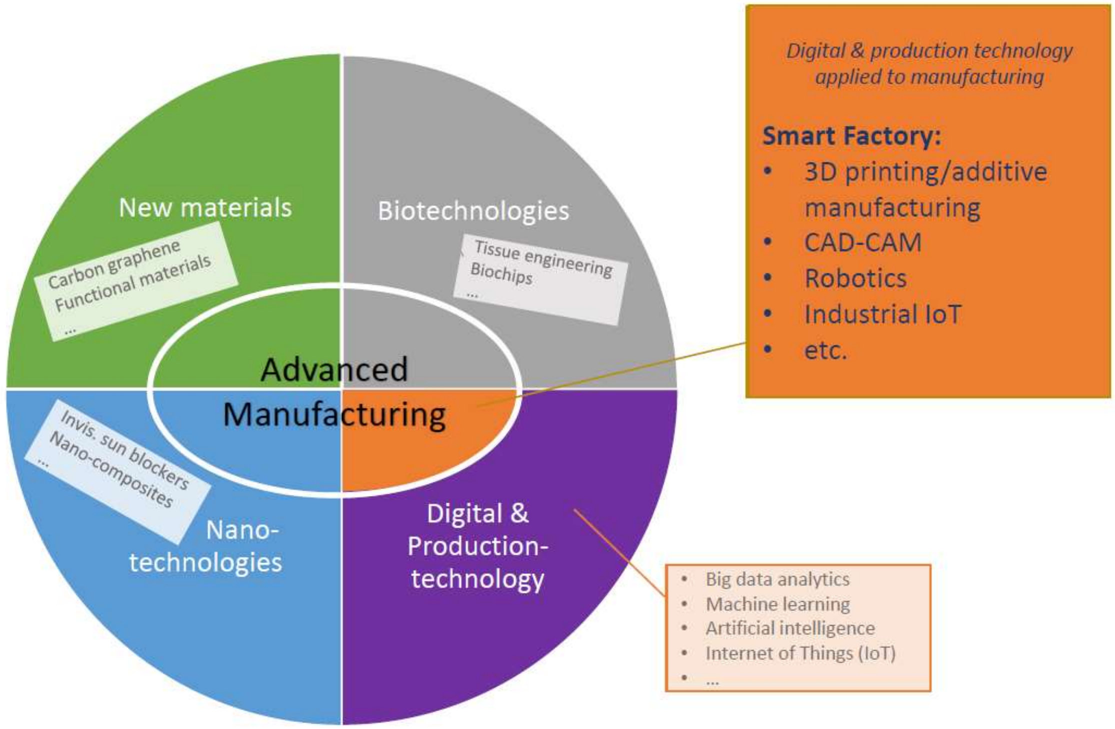


Figure 1.2: New technologies and advanced manufacturing

It should be noted that digital technologies have had a long and successful run within the domain of manufacturing and are thus not limited to the current wave of digital technology. This is an important point: Industry 4.0 refers to a **number of specific digital technology *types***, **but not to *all* digital technology**. It is illustrated in Figure 1.3, which presents the progression from analogue production towards smart digital technologies: starting from analogue production, production processes have become more integrated while also moving away from a partial use of digital and ICT technologies[12] (see Table 1.1 for more details on types of production technologies in manufacturing that can be associated with each of the steps of the pyramid in Figure 1.3.).

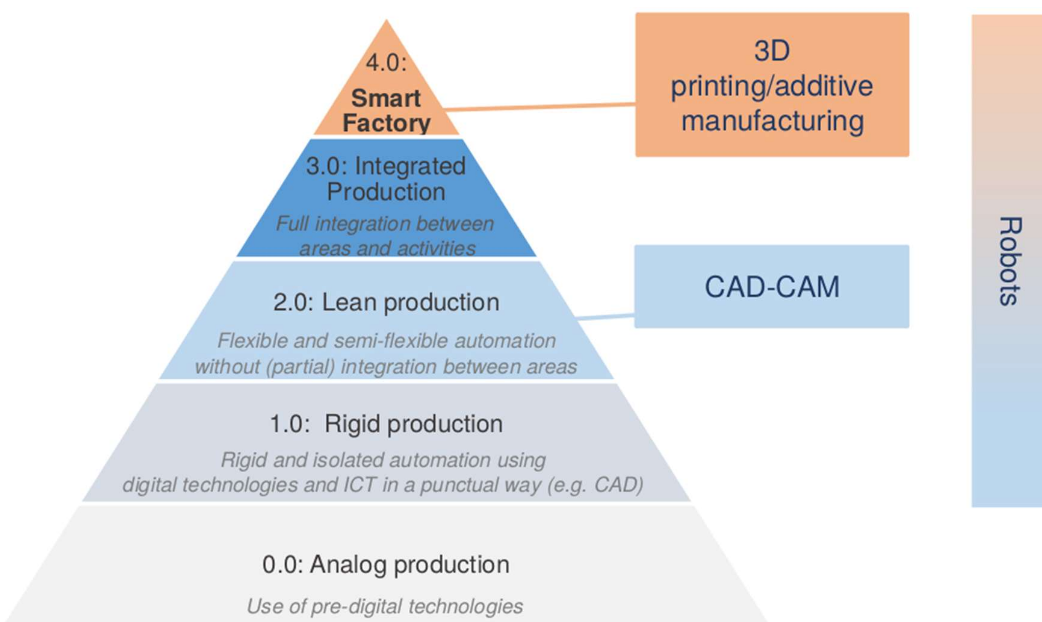


Figure 1.3: Production technologies in manufacturing.

Figure 1.3 also allows us to identify a particular set of very narrowly defined concepts that can be related to (a) particular stage(s) of the digital technology pyramid. For example, the domain of additive manufacturing and 3D-printing is closely related to the smart factory stage. This is because very specific and newly developed materials that belong to the technological frontier are required for the large-scale production of goods through 3D printing (see Figure 1.2). CAD-CAM[13] technologies, on the other hand, allow for a large-scale, computer aided production process within manufacturing, but no fully integrated logistical or digital network linking different areas is required. Lastly, robotics play a key role in digital technologies. (Simple) robots can be used to carry out very rudimentary tasks with little to no complexity in a rigid production process; however (smart) robots also represent an essential building block for smart factories. It is because of this complexity that the adoption of robots and robotics will be addressed later in this module.

Table 1.1: What types of production technologies in manufacturing can be associated with each step of the pyramid in Figure 1.3?

Technology generation	Description
0.0 Analogue production	No digital technologies are used throughout the entire production process (e.g. personal contact with suppliers or via phone; use of machinery that is not micro-electronic based)
1.0 Rigid production	The use of digital technologies is limited to a specific purpose in a specific function and activity (e.g. use of CAD in product development only; use of non-integrated machines operating in isolation)
2.0 Lean production	Digital technologies involve and connect different functions and activities within the firm (e.g. use of CAD-CAM to link up product development and production processes; basic automation)
3.0 Integrated production	Digital technologies are integrated across different activities and functions, allowing for an interconnection of the entire production process (e.g. use of Enterprise Resource Planning (ERP) systems; fully 'paperless' electronic production control systems; industrial and service robots)
4.0 Smart Factory	Digital technologies allow for fully integrated, connected and smart production processes, where information flows across operations and generates real-time feedback to support decision-making processes (e.g. digital twins; real-time sensors and machine-to-machine communication; collaborative robots (cobots); management decision making supported by big data and artificial intelligence)

Source: UNIDO (2020).

Before we turn our attention to robotics, we must understand that these three components are related to a much broader conceptual framework of goods: Figure 1.4 illustrates that the three components represent what this module refers to as *Industry 4.0 goods* which in turn are part of the much broader group of capital goods. This is an important insight as capital goods are of high relevance for a positive development trajectory of the manufacturing industry (Howitt and Aghion 1998; Jorgenson 1963; Williamson 1971). By jointly representing the three dimensions in Figure 1.4 an empirical evaluation of the intensity with which countries lead in a particular capital goods domain and where that places them in a global benchmarking exercise can be conducted. While it would not come as a surprise if a country that is leading in the development and distribution of additive manufacturing technology is also successful in other Industry 4.0 goods, assessing the intensity of a given developing country will certainly be more revealing.

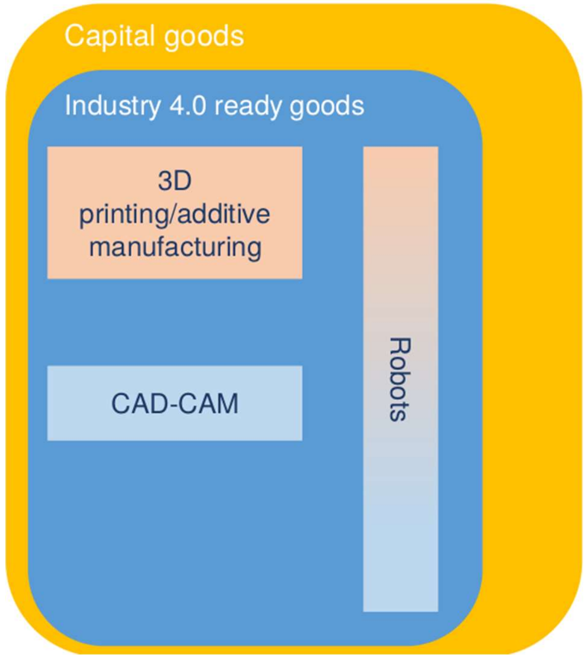


Figure 1.4: The family of capital goods

The successful adoption of production technology in the context of this tool means using all forms of capital goods in the manufacturing production process, be it to produce consumer goods, intermediates or other capital goods. A simple way of finding out whether firms use technology in this way at an aggregate level is to look at their trade flows. As discussed above, machines—and the technology they represent—are often imported as a first step in the adoption process. To determine whether countries are 'users' (importers) or 'producers' (exporters) of such production technology, this EQuIP tool has developed a framework to help policymakers make this determination. This tool can also be used to easily compare these dynamics across countries.

A country is classified as a 'specialized user' of production technology if it imports more goods than the world average; it is classified as 'specialized producer' of production technology if it exports more than the world average. Comparing the resulting figure of capital goods with that of 4.0 goods provides important insights into how a country integrates all vintages of production technology (capital goods) in comparison to 4.0 goods.

Our analysis indicates that only a small number of countries export more capital goods (specifically 4.0 goods) than the world average and are thus coined 'specialized producers'. These are usually high-income countries that are generally considered technology leaders. To be able to put the results into perspective and to compare the country with peer countries, the classification will be based on the country's income group. Some countries' trade behaviour changes over time. This makes for some interesting insights: for example, as countries become wealthier and more technologically developed, imports of capital goods decrease but their exports increase. This indicates that the countries are increasingly developing production technologies themselves.

As our analysis will show, countries that seem to be successfully using (and producing) 4.0 goods also, with very little exception (90 per cent), reveal the same pattern for a broader group of capital goods. This reinforces the approach of depicting technological waves in the form of a pyramid (Figure 1.3). There seems to be little room for skipping individual steps of this technological pyramid. A country generally needs to have a solid manufacturing base in older technologies before it can develop skills and capabilities to use the latest technology.

1.2.3 Robots and job losses in manufacturing

In the past, the adoption of technology through trade dynamics was conceptualized. Now, the consequences of **successful integration** of digital technologies is conceptualized as part of the manufacturing production process.[14] Most new technologies have commercial potentials, such as enhancing a firm's productivity. As discussed above, while the actual displacement effect of manufacturing jobs due to computerization is still subject to debate (Frey and Osborne 2017; Arntz, Gregory, and Zierahn 2016; Nedelkoska and Quintini 2018), what is indisputable is its heterogeneous effect on the workforce, the manufacturing industries and therefore also the countries themselves (Acemoglu and Restrepo 2017, 2018, 2019; Aghion, Jones, and Jones 2017; Bessen and Righi 2019).

To shed light on this dimension, a robot dataset of the International Federation of Robotics (IFR 2019) is used to analyse potential job losses from robotic automation in manufacturing industries. An industrial robot is defined as "an automatically controlled, reprogrammable, multi-purpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications" (IFR 2019, p.7).

Robots are an integral part of the 'smart factory' and are a source for improvements in productivity, especially for routine tasks. This is of particular relevance because routine tasks are especially widespread in manufacturing. This is one part of the argument by Mayer (2018) who points out that one of the two main concerns when thinking about robotic automation is that of technical feasibility: Is it technically possible to replace workers with robots for the particular task under consideration?

There is an additional argument to be made, one of economic feasibility. According to Mayer (2018), three manufacturing sectors with the greatest intensity in routine tasks are food, beverages and tobacco; textiles, apparel and leather; and transport equipment. This means that the technical feasibility of automating workers' routine tasks appears largest in these three sectors. By contrast, the economic feasibility of routine-task automation appears to be greatest in transport equipment, followed by rubber, plastic and chemical products; the electrical and electronics sector; and machinery. The economic feasibility of such automation appears lowest in the textiles, apparel and leather sectors generally classified as low and medium tech.

The number of robots per worker will be combined with the relative size of the given industry and the degree to which robot technologies have moved to maturity or saturation in the countries and industries. These findings will be paired with those on the evolution of the degree of robotization, i.e. the replacement of employees with industry robots, to obtain a clear picture of the potential danger and the severity of the replacement effect a country might face in the context of industrial robotization. The dimensions analysed for this purpose are:

- The share of high risk industries (where worker replacement with smart robots is both technologically and economically feasible and desirable as argued by Mayer (2018)); only a relatively 'high' share of such industries indicates that the configuration of industries is at risk.
- The relative size of manufacturing employment in total employment; only a relatively 'high' share indicates that a large number of workers may be at risk of losing their jobs to smart digital robots.
- The share of robots to employees within manufacturing; only if there are few robots relative to the number of employees will a meaningful displacement effect may occur.[15]

- The degree to which robots are replacing workers; only if there is an active replacement of workers by robots may employees indeed be at risk of losing their jobs. This dimension is captured by looking at the total number as well as at the growth rate of the number of robots per worker considering that the replacement risk depends on how many jobs have already been replaced by robot technologies as well as the pace at which this is happening.[16]

These four different dimensions allow us to develop detailed insights into country-specific dynamics, which will be highlighted in the analytical part of this tool.

1.2.4 Productivity

As already mentioned above, new technologies will only be adopted into the production process if they pay off, i.e. if they increase the productivity of production processes. These technologies will consequently also affect macroeconomic variables such as value added or employment. A sound and feasible way to measure productivity is necessary to analyse the dimension of technology. Only then can productivity dynamics within manufacturing industries and their differences at the industry level as well as across countries be considered.

The key measure of productivity of this tool is labour productivity, which is defined as the ratio of the creation of value added to total employment. In other words, it measures how much value added (in monetary terms) is produced by each employee of a given industry in one year. This tool aims to assess the dynamics of productivity changes over time. This allows for a better assessment of the speed and direction of changes in the sectoral composition of a country's manufacturing industries. The growth rate of productivity can be approximated by the growth rate of value added generation minus the growth rate of employment as depicted in the formula below:

$$growth(Labour\ Productivity) = growth(Value\ added) - growth(Employment)$$

In simpler terms, an increase in productivity will materialize (a positive growth rate) if the same number of workers (an employment growth rate of zero) generates more value added, e.g. by producing more goods (a positive value added growth rate). Conversely, if more employees are needed to produce the same amount of value added, the measured degree of productivity would have declined (negative growth). It is important to note that positive growth rates will be present in all three aggregates if (and only if) $growth(Value\ added) > growth(Employment)$.

1.2.4.1 The concept of *'runner industries'*

These simple premises are presented in Figure 1.5, which illustrates the complex nature of productivity growth dynamics an economy might face: positive productivity growth can either be achieved through a positive and higher growth of value added as well as positive employment growth (also referred to as '**runner industries**') or through positive growth of value added and negative employment growth, which will be referred to as 'jobless growth'.

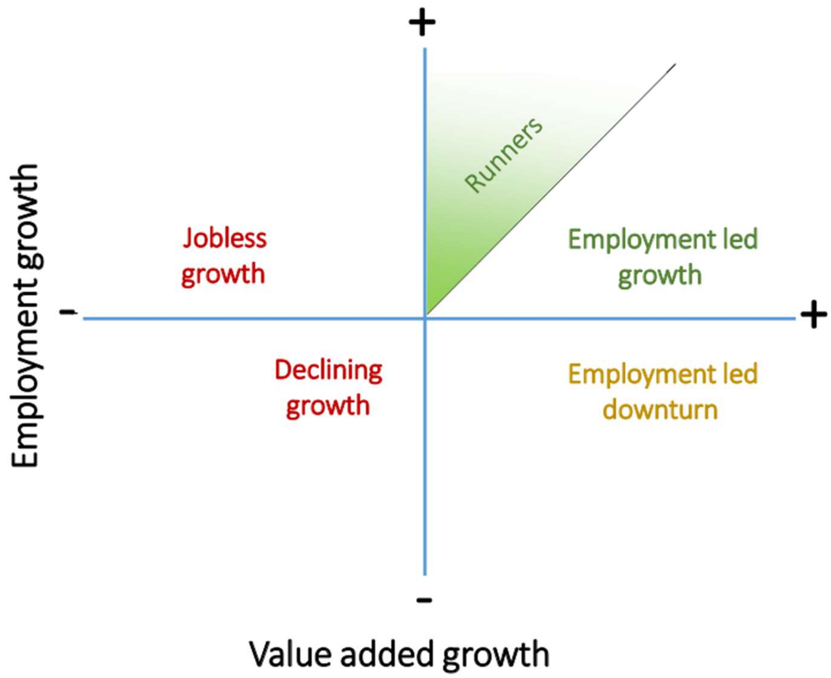


Figure 1.5: Illustration of the runner industry concept

This clearly shows that not all forms of productivity growth are equally desirable, nor are all forms of decline in productivity growth equally bad. The concept of *runner industries* can help policymakers identify the nature of the structural dynamics of specific manufacturing industries. As will be discussed below, the identification of runner industries can be carried out for different time periods, which means that the results may consequently differ. As shown in Appendix B, results like these are by no means contradictory and can instead be used to fully understand an industry's potential trajectory.

1.2.4.2 The concept of *'runner industry exposure'*

After having identified a set of runner industries with particularly positive performance patterns, policymakers should focus their attention on the share of the economy that follows a sustainable growth path in terms of employment and productivity. This dimension is captured through the analysis of *runner industry exposure*. For this, the contribution (share) of runner industries in the manufacturing sector of the given country is investigated.

An analysis of the share of runners is valuable information for policymakers because they can thereby identify jobless growth dynamics as part of the conceptual toolbox. Whether the uptake of Industry 4.0 will be successful in a particular country (and more generally, whether that country will be able to increase its productivity either through capital deepening or other channels), a low share of runners flags a higher vulnerability to undesirable employment dynamics. In other words, countries are more exposed to industries that did not achieve inclusive and tenable growth. Secondly, such an outcome calls for a potential intervention by policymakers to foster inclusive and tenable growth by considering the country-specific characteristics developed in the next section. In this sense, the runner industry classification serves not only as an assessment tool, but also as an early warning tool in the context of much broader policy intervention analysis.

As Appendix C shows, the contribution of runner industries matters at the global level. The share of runner industries in developed countries is notably higher than in developing countries. This is relevant because it demonstrates that rich countries are those with the highest share of sectors characterized by inclusive growth, meaning productivity, employment and manufacturing value added enhancing development. *Countries that became rich followed an inclusive growth path.* This is a crucial message: **economic growth and the adoption of new technologies does not necessarily entail a toll in terms of growth/employment trade-offs.**

Furthermore, runner industries may include low-technology and medium high-technology industries. The fact that rich countries are those with a higher share of runners implies that countries do not have to rely on medium high-technology industries alone to achieve a higher income level. As mentioned earlier, there are different paths to success, and the message seems to be that inclusive growth and structural change within industries play a role as well. This is particularly relevant in the context of the Industry 4.0 debate, as this latest wave of technological advancement will not create technologies that are exclusively confined to the domain of medium-high technology industries but will also find their way to lower technology segments.

1.2.5 Summary

This section has provided a brief overview of the analytical instruments proposed in this tool. The discussion is reflected in Figure 1.6 which illustrates how the dimensions of the analysis are connected: Industry 4.0 focuses on the adoption of new technologies and the effect of robotization in manufacturing.

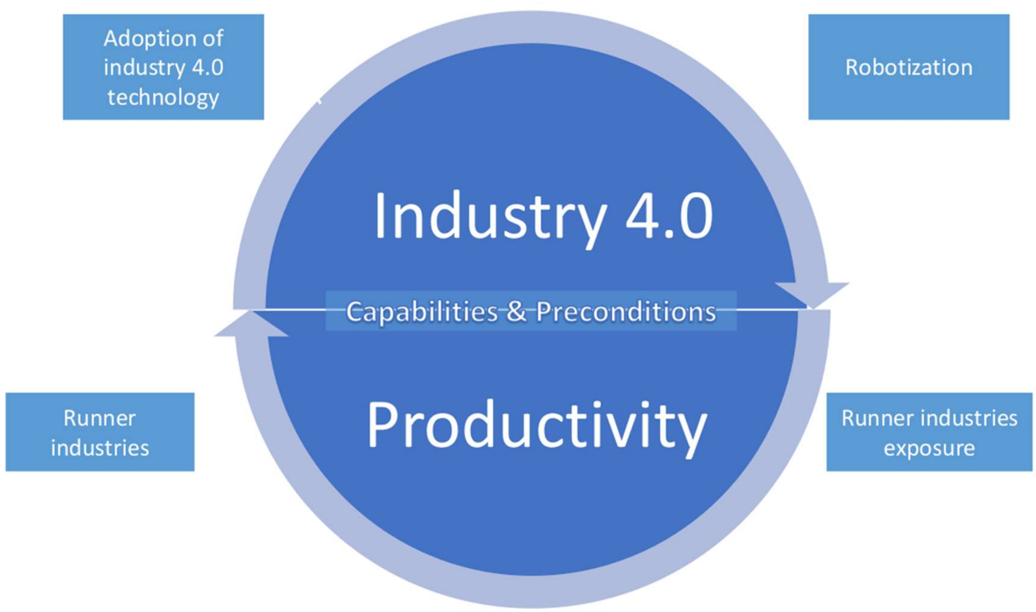


Figure 1.6: Illustration of the dimensions of the analysis

As regards productivity, the link between robotization, high-technology and runner industries (linking Industry 4.0 technology with productivity) was emphasized and attention was called to the fact that countries with the highest share of runners, i.e. advanced economies, lead in the trade and creation of advanced manufacturing technologies.

As the empirical section of this report will show, there is very high correlation between the dimension of Industry 4.0 (and new technologies as a whole) and that of productivity: those industries that face a higher risk of robotization according to Mayer (2018) also by and large belong to the group of industries that the OECD (2011) classifies as medium high-technology industries. More interestingly, this classification of medium high-technology industries depends on their R&D expenditure. That is, these industries have prioritized investments in the development of new and the refinement of already existing technologies. Based on our earlier discussion, the overlap between these industries and those driven by AI (Calvino et al. 2018; Vincent, Vertesy, and Damioli 2019) should also be obvious.

Have these higher technologically-based industries been the ones that have most significantly been affected by employment displacement? As discussed previously, Industry 4.0 technologies could definitely present a challenge for policymakers in the future, automatization has always been a central component of the manufacturing process and has been of utmost importance for capital-intensive industries with high(er) technological sophistication. By using the concept of runner industries, the characteristics of these industries can be easily and conveniently quantified: have these industries experienced the highest level of job losses due to automatization? Or have they not only displaced workers but also created new jobs as a consequence of their technological advancement?

As our runner analysis demonstrates, the latter has been the case: there is a notable overlap between R&D-heavy industries and runner industries. While it is true that this group of industries is more likely to be affected by computerization (Mayer (2018)), this same group of industries has also followed the most robust, sustainable and inclusive growth path. To this end, the golden thread of 'creation through destruction' not only sews together the empirical analysis of this tool, it is also closely tied to the findings of the automation literature discussed earlier (Acemoglu and Restrepo 2017, 2018, 2019; Aghion, Jones, and Jones 2017, among others): Technological advancements are very likely to increase social inequality in the short run; however, they also create conditions under which stable equality can be achieved in the long run. Consequently, policymakers need not only be made aware of these dynamics, they also need the appropriate tools to assess and deal with the challenges the current revolution of smart digital technologies brings.

2. Methodology

This section introduces a number of indicators that will be used in the ensuing sections to analyse the following strategic questions:

- How successful is a country's adoption of new technologies—in general and in Industry 4.0 in particular—in absolute and in relative terms?
- What would a reasonable target be for a country that has fallen behind in terms of adoption rate to catch up?
- How does a country's industrial automation capacity respond to newly emerging technologies?
- How can we assess whether a country's industrial automation capacity has improved?
- To what extent are manufacturing jobs in the country at risk of being replaced by robotic automation?
- What are the productivity growth dynamics of a given industry and what do they depend on?
- Are positive productivity growth rates always good?
- Do industries exist that offer positive growth and employment prospective in recent periods of global market integration and fast-paced technological advancements?
- What is the exposure of a country to industries that have experienced positive employment, value added and productivity growth in the past?
- How does the share of these industries evolve over time?

The main data sources are UN COMTRADE (2019) for data on imports and exports of goods, UN INDSTAT (2019) for data on employment and value added at the industry level, the World Bank World Development Indicators (WDI 2019) for information on a country's total employment, population and nominal gross domestic product and the International Federation of Robotics (IFR 2019) for the stock of industrial robots. For total manufacturing employment, data from the International Labour Organisation (ILO 2019) is used. Alternatively, the reader can aggregate industry employment based on UN INDSTAT (2019). This alternative is further discussed in the appendix.

In this section, the index ***i*** refers to a country, ***j*** refers to an industry, ***k*** denotes a product or product group, while ***t*** denotes a time period (usually, one year).

2.1 Adoption of new technologies

As technology is a main driver of economic development by increasing productivity, the country's current stage of adoption is of relevance. If it is a leader in technology, for example, one would expect it to also be an exporter of the respective goods related to that technology. One way of determining whether a country has successfully adopted new technologies is if it actually exports them.

To become a technology leader, most countries first start by importing technology to adopt it and absorb it. This section begins by looking at the share of imports and exports of the broadest category of relevant goods and capital goods and subsequently analyses Industry 4.0 goods. That is, we first focus on goods related to all vintages of technology and then turn our attention to goods related to the current wave of innovation.

Data on the share of imports and exports is combined to determine the country's stage of technology adoption.

2.1.1 Share of capital goods imports

Starting with capital goods, we explore the share of imported capital goods to the country's total imports. This is a first indication of a country's ability to use these goods and the technology related to them.

Main question

- Of all the goods imported by a country, what is the share of capital goods?

For a given country ***i***, product group ***k*** (capital goods) and period ***t***,

$$Share\ of\ capital\ goods\ imports\ in\ total\ imports_{it} = \frac{Imports_{ikt}}{Total\ imports_{it}}$$

which indicates the share of imported capital goods in all imported goods.

Data sources

The data sources for this indicator are provided in Table 2.1. Data on imports are taken from UN COMTRADE (2019), which provides different classifications of goods. 'BEC' is chosen as it is a classification that defines broad economic categories, such as capital goods (United Nations Trade Statistics 2003). For a more detailed description of the 'BEC' classification, see H in the appendix.

Table 2.1: Adoption of technologies embodied in capital goods

Indicator	Variable	Source
Share of imported capital goods in total imports	A country's capital goods imports	UN COMTRADE (2019) BEC
	A country's total imports	UN COMTRADE (2019) BEC

2.1.2 Share of capital goods exports

While imports may indicate the ability to use capital goods, exports denote the extent to which a country is competitive enough to be able to export capital goods to the world market.

Main question

- Of all the goods exported by the country, what is the share of capital goods?

For a given country ***i***, product group ***k*** (capital goods) and period ***t***,

$$Share\ of\ capital\ goods\ exports\ in\ total\ imports_{it} = \frac{Exports_{ikt}}{Total\ exports_{it}}$$

which indicates the share of exported capital goods in all exported goods.

Data sources

The data sources for this indicator are provided in Table 2.2. Data on exports are taken from UN COMTRADE's (2019) 'BEC' classification.

Table 2.2: Exports of capital goods

Indicator	Variable	Source
Share of exported capital goods in total exports	A country's capital goods exports	UN COMTRADE (2019) BEC
	A country's total exports	UN COMTRADE (2019) BEC

2.1.3 Revealed comparative advantage of capital goods imports

The simple share of a country's imports of capital goods is an initial very broad indicator of potential technology adoption by importing such goods. Next, we want to establish whether a country is adopting new technologies through imports or whether it is already producing such goods themselves needs to be determined. This requires determining whether the country is importing more or less than the world average. The country's share of capital goods imports is compared to the share of global capital goods imports. This indicator is referred to as 'revealed comparative advantage (of imports)' (RCA). If this indicator is higher than 1, the country imports relatively more capital goods than the average country.

Main question

- Does a country import more or less capital goods than the global average?

$$RCA\ import\ of\ a\ country_{ikt} = \frac{\frac{Imports_{ikt}}{Total\ imports_{it}}}{\frac{Imports_{wkt}}{Total\ imports_{wt}}}$$

$Imports_{wkt}$ denotes world imports of capital goods, while $Total\ imports_{wt}$ represents total world imports of all goods.

Data sources

Table 2.3: RCA imports of capital goods

Indicator	Variable	Source
A country's RCA in imports of capital goods	A country's Imports of capital goods	UN COMTRADE (2019) BEC
	A country's total imports	UN COMTRADE (2019) BEC
	Total global imports of capital goods	UN COMTRADE (2019) BEC
	Total global imports	UN COMTRADE (2019) BEC

2.1.4 Revealed comparative advantage of capital goods exports

Once we know whether a country imports more or less capital goods than the world average, we can combine this information with the export side. If, for example, a country imports less than the global average, but exports more than the world average, the difference is being domestically produced. This would imply that the country's adoption of new technology has been so successful that it can actually export it.

Main question

- Does a country export more or less capital goods compared to the global average?

$$RCA\ export\ of\ a\ country_{ikt} = \frac{\frac{Exports_{ikt}}{Total\ exports_{it}}}{\frac{Exports_{wkt}}{Total\ exports_{wt}}}$$

Data sources

The data sources are the same as above, UN COMTRADE's (2019) 'BEC classification'.

Table 2.4: RCA exports of capital goods

Indicator	Variable	Source
A country's RCA in exports of capital goods	A country's capital goods exports	UN COMTRADE (2019) BEC
	A country's total exports	UN COMTRADE (2019) BEC
	Total global exports of capital goods	UN COMTRADE (2019) BEC
	Total global exports	UN COMTRADE (2019) BEC

An additional interpretation must, however, be pointed out. A country can be a below-average exporter of capital goods. This does not mean that the country has not yet successfully adopted the related technology. It might mean that it uses the imported capital goods to produce other goods and the country might even export these other goods. Not every successful technology adopter becomes an exporter of capital goods. In simple terms: not all machines (and the technology embedded in them) are used to produce other machines. However, the analysis which is part of the module will show that different income groups display distinct patterns.

2.1.5 Share of imported 4.0 goods

The previous indicators introduced a way of analysing the share of imports and exports of capital goods, goods that represent every type and wave of technology. Now the focus will shift Industry 4.0 goods. The proposed indicators are equivalent to the ones presented above.

Main question

- What is the share of 4.0 goods in a country's total imports?

For a given country ***i***, product group ***k*** (4.0 goods) and period ***t***,

$$Share\ of\ 4.0\ goods\ imports\ in\ total\ imports_{it} = \frac{Imports_{ikt}}{Total\ imports_{it}}$$

Data sources

The data sources for this indicator are provided in Table 2.5. UN COMTRADE (2019) with the HS 2002 classification is used, as we are now interested in specific products. The list of products is based on UNIDO (2020) and can be found in Table F.1.

Table 2.5: Adoption of Industry 4.0 technologies

Indicator	Variable	Source
The share of imported Industry 4.0 goods in total imports	A country's imports of 4.0 goods	UN COMTRADE (2019) HS 2002
	A country's total imports	UN COMTRADE (2019) HS 2002

2.1.6 Export share of 4.0 goods

Main question

- What is the share of 4.0 goods in a country's total exports?

For a given country ***i***, product group ***k*** (4.0 goods) and period ***t***,

$$Share\ of\ 4.0\ goods\ exports\ in\ total\ imports_{it} = \frac{Exports_{ikt}}{Total\ exports_{it}}$$

Data sources

The data sources for this indicator are provided in Table 3.6.

Table 2.6: Exports of Industry 4.0 technologies

Indicator	Variable	Source
Share of exported Industry 4.0 goods in total exports	A country's exports of 4.0 goods	UN COMTRADE (2019) HS 2002
	A country's total imports	UN COMTRADE (2019) HS 2002

2.1.7 Revealed comparative advantage of imported 4.0 goods

Main question

- Is a country importing more or less 4.0 goods compared to the global average?

$$RCA\ import\ of\ a\ country_{ikt} = \frac{\frac{Imports_{ikt}}{Total\ imports_{it}}}{\frac{Imports_{wkt}}{Total\ imports_{wt}}}$$

where $Imports_{wkt}$ denote global imports of 4.0 goods, while $Total\ imports_{wt}$ represents total world imports.

Data sources

Data are taken from UN COMTRADE (2019) (HS 2002 classification).

Table 2.7: RCA imports of Industry 4.0 goods

Indicator	Variable	Source
A country's RCA in imports of 4.0 goods	A country's imports of 4.0 goods	UN COMTRADE (2019) HS 2002
	A country's total imports	UN COMTRADE (2019) HS 2002
	Total global imports of 4.0 goods	UN COMTRADE (2019) HS 2002
	Total global imports	UN COMTRADE (2019) HS 2002

2.1.8 Revealed comparative advantage of exported 4.0 goods

Main question

- Does a country export more or less 4.0 goods compared to the global average?

$$RCA\ export\ of\ a\ country_{ikt} = \frac{\frac{Exports_{ikt}}{Total\ exports_{it}}}{\frac{Exports_{wkt}}{Total\ exports_{wt}}}$$

Data sources

Data is taken from UN COMTRADE (2019) (HS 2002 classification) as the focus is on specific goods (Table F.1).

Table 2.8: RCA exports of industry 4.0 goods

Indicator	Variable	Source
A country's RCA in exports of 4.0 goods	A country's exports of 4.0 goods	UN COMTRADE (2019) HS 2002
	A country's total exports	UN COMTRADE (2019) HS 2002
	Total global exports of 4.0 goods	UN COMTRADE (2019) HS 2002
	Total global exports	UN COMTRADE (2019) HS 2002

After the RCAs for imports and exports have been determined, they can be used to classify countries according to their technology adoption. Trade flows 'reveal' the behaviour of firms. Countries are classified according to their trade patterns, e.g. whether they are above or below average importers or exporters.

Box 2.1: Alternative identification and disaggregation

All shares discussed above could alternatively be calculated as shares in production by using nominal gross domestic product (GDP) in the denominator instead of total imports or exports. Nominal GDP is available from the World Bank's 'World Development Indicators' (WDI 2019). The resulting indicator can be applied as a second benchmark to assess whether a country imports more or less than comparator countries. If a country's share of imports is generally higher than its peers, looking at imports of 4.0 goods in total imports could understate the expenditures in this product group.

Moreover, the above indicators can be used to disaggregate data further, for example, to specific goods, such as CAD-CAM or robotics. This would potentially reveal countries' specialization in very specific technologies or goods.

2.2 Robots and job losses in manufacturing

An important questions that arises with every technological revolution is whether it will substitute labour. One of the main topics of discussion is whether jobs will be lost to robotic automation. Before an assessment can be made about the potential risks of the newest technology, indicators that capture the use of robots, as well as how many people are potentially at risk of being replaced need to be introduced. To this end, the indicators described below must be combined.

Box 2.2: Recommendation on aggregated employment measure

This section uses manufacturing employment at the aggregated sector level (for manufacturing as a whole) as well as employment figures at the industry-level within manufacturing following the ISIC rev. 3 classification. While we resort to INDSTAT (2019) data for the industry-level analysis, it is recommended to use ILO (2019) data when analysing the manufacturing sector aggregate. In what follows, we introduce both data sources and demonstrate that there are only marginal qualitative differences across both data sources.

2.2.1 Robot intensity

Robots are used as supplements or substitutes for human labour. Instead of using absolute stocks, robot intensity is defined as the stock of robots per manufacturing job. If this number is increasing, more robots are being used for the same amount of human labour (or the same number of robots with less human labour). To distinguish the two possible interpretations, the development of employment as a whole will be taken into account later.

Main question

- How many industrial robots are being used compared to manufacturing employees?

$$Robot\ intensity_{it} = \frac{Industrial\ robot\ operational\ stock_{it}}{Manufacturing\ employment_{it}}$$

Data sources

Data sources for this indicator are the IFR (IFR 2019) for the stock of industrial robots used in all manufacturing industries and ILO data (2019) for employment in all manufacturing industries.

Table 2.9: Robot intensity in a country

Indicator	Variable	Source
Robot intensity within manufacturing	Industrial robot operational stock used by all industries	IFR (2019), World Robotics
	Manufacturing employment	ILO (2019) or UN INDSTAT (2019)

2.2.2 Growth rate of robot intensity

To determine whether robot intensity has increased or decreased over time, it makes sense to calculate annual growth rates. This figure illustrates the extent to which robot intensity has increased or decreased from one year to the next. It will be used in the empirical analysis below to ascertain whether some countries are showing signs of maturity or saturation. That is, low annual growth rates indicate that the number of robots per worker has not increased significantly. This must be taken into account when assessing the risk of automation.

Main question

- By how much did robot intensity grow or decrease per year?

$$Annual\ growth\ rate\ of\ robot\ intensity_{it} = \frac{End\ value_{it} - Initial\ value_{it}}{Initial\ value_{it}}$$

2.2.3 Robot intensity by industry

Robots are used in different industries to varying degrees. Some industries use more, some use only very few robots compared to the number of employees. To determine how countries use robots in different industries over time, robot intensity is calculated by industry.

Main question

- How many industrial robots are being used compared to manufacturing employees in different industries ***j***?

$$Robot\ intensity_{ijt} = \frac{Industrial\ robot\ operational\ stock_{ijt}}{Manufacturing\ employment_{ijt}}$$

Data sources

The data sources for this indicator are the IFR (IFR 2019) for the stock of industrial robots for a specific industry and UN INDSTAT (2019) for employment in that industry.

Table 2.10: Robot intensity in a country by industry

Indicator	Variable	Source
Robot intensity within manufacturing	An industry's industrial robot operational stock	IFR (2019), World Robotics
	Manufacturing employment of that same industry	UN INDSTAT (2019)

2.2.4 Share of employees in risk industries

Now that indicators for the use of robots per employee have been introduced, we can address the question if and to what extent workers are at risk of losing their job due to robotic automation. Arguably, not every type of job faces the same risk of being replaced by a machine. Mayer (2018) has identified four manufacturing industries in which this risk is particularly high. They are labelled 'risk industries' and they are: chemicals, rubber and plastic; electronics and the automotive industry. (see Section 4.1.2 for a detailed discussion).

Main question

- What is the share of workers in risk industries in total manufacturing employment?

$$Share\ of\ employm.at\ risk\ in\ total\ manufac._{ijt} = \frac{Manufact.\ employment\ in\ risk\ industries_{ijt}}{Total\ manufacturing\ employment_{it}}$$

Data sources

The data sources (Table 2.11) is UN INDSTAT (2019) for sectoral employment and the ILO (2019) for total manufacturing employment.

Table 2.11: Share of employment in risk sectors

Indicator	Variable	Source
Share of employment at risk in total manufacturing	Manufacturing employment in risk industries: electronics, automotive and rubber	UN INDSTAT (2019)
	Total manufacturing employment	ILO (2019) or UN INDSTAT (2019)

2.2.5 Share of manufacturing employment in total employment

Next, the share of workers in manufacturing industries in total employment is calculated. This indicates one important dimension of the manufacturing sector for the economy. If the manufacturing sector as a whole is small, then automation is likely to affect fewer people.

Main question

- What is the share of workers working in the manufacturing industry compared to total employment in a country?

$$Share\ of\ manufac.\ employment\ in\ total\ employment_{it} = \frac{Total\ manufacturing\ employment_{it}}{Total\ employment_{it}}$$

Data sources

The data sources (Table 2.12) are UN INDSTAT (2019) for industry employment and the World Bank's 'World Development Indicators' (WDI 2019) for a countries' total employment.

Table 2.12: Share of manufacturing employment

Indicator	Variable	Source
Share of manufacturing employment in total employment	Total manufacturing employment	ILO (2019) or UN INDSTAT (2019)
	Total employment	WDI (2019)

2.3 Productivity

The analysis of productivity-related dynamics entails two consecutive steps.

- In **Step 1**, the three key variables of the analysis (productivity, employment, value added) are used to analyse industry-level growth dynamics and follow an inclusive and tenable growth trajectory (a positive growth rate of value added, employment and productivity). Throughout the analysis, we refer to these industries as 'runners' (or runner industries).
- In **Step 2**, the share of runner industries relative to a country's manufacturing sector is assessed. Thereby the share of a country's manufacturing industry, characterized by positive productivity, value added and employment dynamics, can be quantified.

See Table 2.13 for a list of relevant variables. Calculations in this section only use INDSTAT (2019) data.

Table 2.13: Structure of analysis

Indicator	Variable
Step 1: Identification of runner industries	Productivity CAGR
	Employment CAGR
	Value added CAGR
Step 2: Runner industry exposure	Value added share of runner sub-sectors
	Employment share of runner sub-sectors

2.3.1 Identification of runner industries

Strategic questions and data sources

- What are a given industry’s productivity growth dynamics and what do they depend on?
- Are positive productivity growth rates always good?
- Do industries exist that provide a positive growth and employment prospective, even during the most recent periods of global market integration and fast-paced technological advancements?

The indicators used for this analysis are the sub-sector value added and employment series from INDSTAT (2019), both of which are used to calculate the third indicator (productivity) as described in Table 2.14.

Table 2.14: Data sources for identification of inclusive and tenable industry growth

Indicator	Variable	Source
Employment growth rate	Sub-sector employment-to-population compound annual growth rate (CAGR)	UN INDSTAT (2019)
Value added growth rate	Sub-sector value added per capita (VA) compound annual growth rate (CAGR)	UN INDSTAT (2019)
Productivity growth rate	Sub-sector productivity growth rate (CAGR)	(calculated based on variables above)

Methodological underpinnings of runner identification analysis

The purpose of this step is to illustrate the effect of (changes in) productivity dynamics and how they relate to economy-wide performance patterns. The subsequent analysis is conducted on the basis of the compound annual growth rate (CAGR), which is calculated as

$$CAGR = \frac{End\ value}{Initial\ value}^{\frac{1}{no.\ of\ years}} - 1$$

The CAGR corresponds to a smoothed annual average over the time period being considered. It serves as a measure to illustrate how much a particular variable has increased over time. In this tool, productivity is defined as the ratio of value added creation over the employment head count. In other words, it measures how much value added (in monetary terms) is produced by each employee of a respective industry in one year. While this measure is interesting, this module seeks to assess the dynamics of productivity changes over time. This allows for better assessment of the speed and direction of changes in the sectoral composition of a country’s manufacturing industries.

It is preferable to calculate productivity and value added growth rates based on real value added series. This is because nominal value added growth is a composition of the growth rates of both real value added **and** of prices, i.e. inflation. Calculating nominal value added growth rates could therefore result in unrealistically high (nominal) growth rates, which are simply the result of high inflation. Obviously, this is not desirable. In Appendix E, a simple and straightforward measure to calculate real value added series for manufacturing industries is proposed.

Based on this formula, CAGRs for productivity, value added and employment can be calculated. As discussed in Section 1.2.4, some combinations of growth rates of these three variables are more desirable than others. Section 5.1 will focus on the analysis of industries with a positive value added and productivity growth, i.e. industries that can be classified as **runner industries**.

For an in-depth analysis of runner industry heterogeneity patterns, the previously obtained growth rates can be plotted in a histogram to illustrate differences across countries and to understand where a particular group of countries lies in relation to the other industries.

2.3.2 Runner industry exposure

Strategic questions and data sources

- What is the exposure of a country to industries that have experienced positive employment, value added and productivity growth in the past?
- How does the share of these industries evolve over time?

The variables necessary to calculate runner industry exposure shares are listed in Table 2.15.

Table 2.15: Indicators for identifying exposure to runner industries

Indicator	Variable	Source
Runner value added share	Manufacturing value added of runner sub-sectors	UN INDSTAT (2019)
	Total manufacturing value added	UN INDSTAT (2019)
Runner employment share	Manufacturing employment of runner sub-sectors	UN INDSTAT (2019)
	Total manufacturing employment	UN INDSTAT (2019)

The shares for value added and employment are then calculated as

$$Runner\ value\ added\ share_{it} = \frac{Value\ added\ runner\ industry_{it}}{Total\ manufacturing\ value\ added_{it}}$$

$$Runner\ employment\ share_{it} = \frac{Employment\ runner\ industry_{it}}{Total\ manufacturing\ employment_{it}}$$

In the two equations above $Total\ manufacturing\ value\ added_{it}$ and $Total\ manufacturing\ employment_{it}$ refer to the sum of value added and/or employment over all available industries on the basis of the previously calculated data series. In other words, both denominators are **not** obtained from the pre-aggregated manufacturing sector series. Runners can be identified at the global, income group and country level. Shares can be calculated accordingly on that basis.

3. Adoption of new technologies

As regards the generation of new technologies, economies can either create these themselves or import them. It has been widely established in economic research that the latter is more common.[17] Consequently, it makes sense to investigate the trade dynamics between economies, i.e. import and export flows. Different speeds and intensities of technology adoption across countries and over time can be thereby highlighted.

However, the mere adoption of new technologies through importation does not guarantee local absorption and diffusion. For this to be a successful strategy, preconditions that create a growth-enabling environment of a country matter:[18] the most recent Industrial Development Report (UNIDO 2020) also focuses on Industry 4.0 using new firm level data. It emphasizes the necessity of certain pre-requisites to be met if firms are to successfully adopt new (digital) technology. They range from institutional and infrastructure capabilities such as energy supply and connectivity, to production and technological capabilities such as skilled staff that can operate machines and software, to changes in a firm's culture, such as acceptance of increased automation in the production process. Imports of technology can additionally strengthen these capabilities, as learning processes are related to trade. These can be derived from cooperation with universities or foreign partners, or from reverse engineering, just to name a few.

For the purposes of this tool, a heterogeneous group of countries is considered. This group consists of a set of advanced economies (Germany, Japan and the Republic of Korea), all of which are big players in the adoption and generation of new technologies (see Appendix A). The list of countries is complemented by a group of emerging economies (China, the Russian Federation as well as Viet Nam and Georgia). These countries have been selected with the purpose of illustrating specific development patterns observed in the adoption strategies of Industry 4.0 technologies.

As the previous discussion showed, Industry 4.0 technologies are a sub-group of capital goods. Whereas the former identify cutting-edge technologies that are most likely found in modern, state-of-the-art manufacturing facilities, capital goods cover a much broader domain. Capital goods are machinery and other manufactured goods used by industry, government and non-profit private institutions. They are in fact producers' goods that are defined as part of fixed capital formation (United Nations Trade Statistics 2003).

Capital goods form one of the central building blocks of a healthy and growing manufacturing sector: economic research shows that manufacturing provides great potential for positive growth trajectories through its scalability and high degree of capital accumulation, both of which can be identified through the utilization of capital goods. Consequently, the analysis begins at the level of capital goods, which can be understood to represent both the latest as well as more established production technologies. The same tools are then applied to the sub-group of Industry 4.0 goods, which allows identification of Industry 4.0-specific dynamics. The goal here is to provide a simple tool for policymakers to analyse and categorize where their economy stands relative to other economies and the global level, both in terms of the utilization of capital goods as well as Industry 4.0 technology as part of the domestic production process. Different income groups of countries (high-income, upper middle-income, lower middle-income and low-income) reveal distinct trade patterns with regard to imports and exports of production technology.

3.1 Capital goods

The first graph (Figure 3.1) presents shares of imports of capital goods in all goods (indicator 2.1) between 2002 and 2017. Considering the entire time period, only the Russian Federation's import share increased significantly. What might be surprising is that there is no clear division between high-income countries and the others. For example, Japan as well as Georgia had decreasing shares of imports of capital goods until the middle of the last decade when those shares began to increase again.

Decreasing import shares, on the one hand, can mean that relatively fewer capital goods are imported because a country is able to produce them domestically. On the other hand, rising import shares may imply that a country is increasingly able to use goods that are related to some technology.

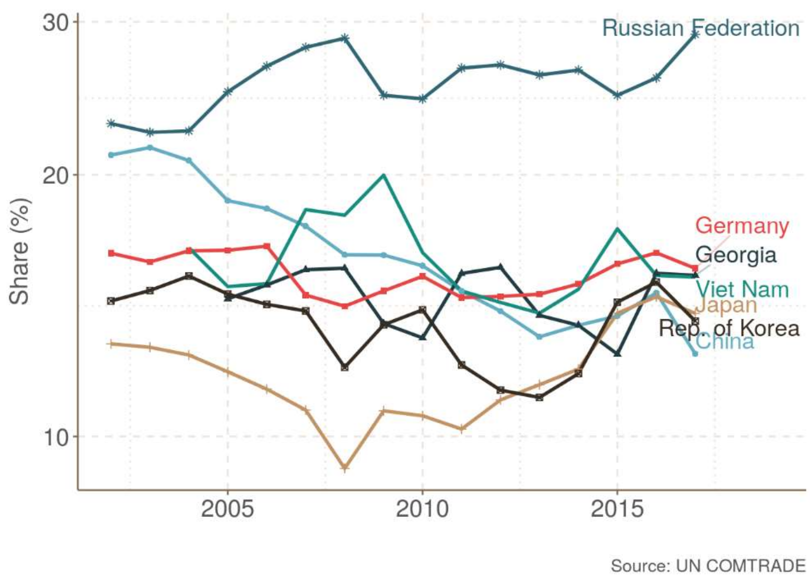


Figure 3.1: Share of capital goods imports in total imports

While imports can represent users of production technologies, exports can represent producers (indicator 2.2).

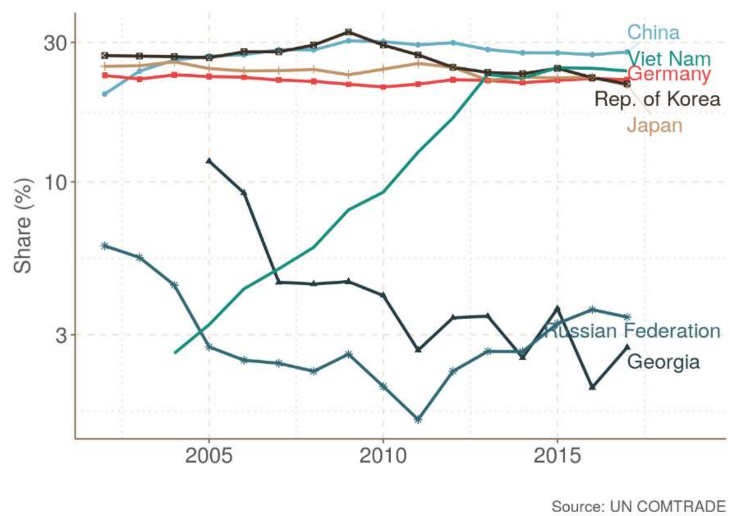


Figure 3.2: Share of capital goods exports in total exports

Figure 3.2 shows that there are countries such as Japan, the Republic of Korea, Germany or China, in which capital goods make up one-third of the countries' total exports, while the share of capital goods in exports decreased in others, such as the Russian Federation or Georgia. Viet Nam seems to have transformed into an exporter in the last ten to 15 years. Since the figures represent production technology of all vintages, we cannot yet see who the technology leaders are in terms of new technological advancements. This will be achieved by examining imports and exports of 4.0 goods below.

An immediate question arising from this initial analysis is how policymakers can obtain a benchmark of their country's performance patterns in relation to global dynamics. We propose two indicators to achieve this objective: by calculating the import shares relative to the world average (indicator 2.3), a country's import performance in relation to the global average can be quantified. This relationship is referred to as the 'revealed comparative advantage' (RCA). If a country has an import RCA that is larger than 1, it imports more than the world average. This, in turn, may point to a faster adoption of technology for countries that have not yet reached the technological frontier. In that sense, the RCA of imports (indicator 2.3) is strongly connected to the adoption rate (indicator 2.1), as both indicators depend on the share of capital goods in total imports. The two indicators may exhibit the same overall import profiles across countries, but the interpretation changes, as RCA is a relative measure.

The second indicator, RCA exports (indicator 2.4), serves as a key measure to determine countries' local capabilities in producing capital goods. As before, if a country is characterized by an RCA (export) larger than 1, it exports more than the global average. This means that it has acquired capabilities to export sophisticated and technology-intensive goods and is competitive on the global stage.

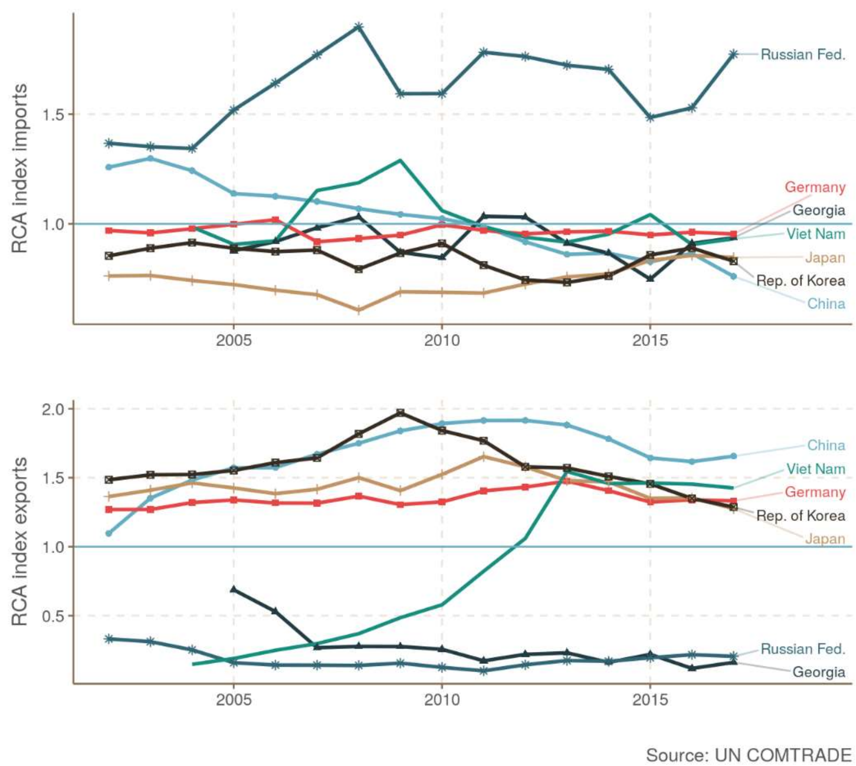


Figure 3.3: Revealed comparative advantage, imports and exports of capital goods

Figure 3.3 presents an interesting picture. It displays countries that import or export capital goods more or less than the world average. When this information is combined, a story about technology adoption based on 'revealed' trade flows can be told.

Let us look at some examples: the Russian Federation is the only country in our sample that clearly imports more capital goods over time than the world average (upper graph), but also exports much less than the world average (lower graph). This implies that the Russian Federation uses capital goods and the accompanying technologies in their production process, but it is not an above average exporter of capital goods. This is either because (i) they have not yet adopted and absorbed the technology to an extent that allows them to become exporters of capital goods or (ii) they only produce for the domestic market, or (iii) they use the production technology to produce and export other (non-capital) goods. Indicators from other EQuIP tools could help shed more light on the specifics.

Similar to the Russian Federation, Georgia also shows a low export of capital goods compared to the world average. However, Georgia also does not import significantly more capital goods than the world average (although it is close to the average). This most likely points to the fact that Georgia is not yet able to adopt all of the technologies associated with capital goods. The rest of the countries' developments are relatively similar. Over time, they import less capital goods than the world average. While China's share decreased continuously, that of other countries have been relatively stable over the years. At the same time, they export more than the world average. This implies that these countries are producing capital goods themselves. This is another indicator of successful technology adoption, in the sense that they no longer need to import production technology but have become producers.

Based on the indicators discussed above, we can create a classification of the different groups.

RCA import	RCA export	Group
< 1	> 1	specialized producer
> 1	> 1	specialized producer and user
> 1	< 1	specialized user
< 1	< 1	non-specialized

Here, 'specialized producer' refers to countries with RCA imports of below (or close to) 1 and RCA exports that are greater than 1. These countries have a revealed comparative advantage in exporting goods (but not in importing them) and are typically those closest to the technology frontier.

Following the specialized producers are economies that are 'specialized producers and users' with a comparative advantage in both importing and exporting. Despite the fact that these countries have RCA imports and exports greater than 1, they most likely do not import the same set of goods as they export. This means that if such a country is identified for, say, capital goods, it makes sense to 'dig deeper' and look at what kind of capital goods the country imports and exports. This is where differences will most likely arise: a country may be a strong exporter of some groups of goods, while it may still be an importer when it comes to the adoption of the latest available technology. This can be determined by analysing RCAs of Industry 4.0 goods below. China, for example, followed the pattern described above at the beginning of the period, but continuously decreased its share of capital goods imports. The third group, which consists of 'specialized users', includes countries with an RCA imports share that is larger than 1 and RCA exports smaller than 1. These countries typically try to adopt new technologies through imports and absorption. The Russian Federation is an example of such a country in our sample. Lastly, countries with RCAs below 1 are non-specialized, at least not yet.

This classification of countries based on trade flows of capital goods can help policymakers, first, determine whether they are users or producers of production technology. Second, it can be used as a benchmarking exercise in technology adoption because the classification is closely related to income groups defined by the World Bank (2019).

Figure 3.4 clearly illustrates that RCA exports of capital goods are widely distributed: high-income countries have the highest RCAs exports, on average, followed by upper middle, lower middle and finally low-income countries. As for RCA imports, we observe that import propensity, on average, seems to first build up as economies grow richer but declines once the country has reached the lower middle-income mark. It must be noted, however, that for all four income group aggregates, the differences are both relatively minor and centre around the global average mark of '1'.

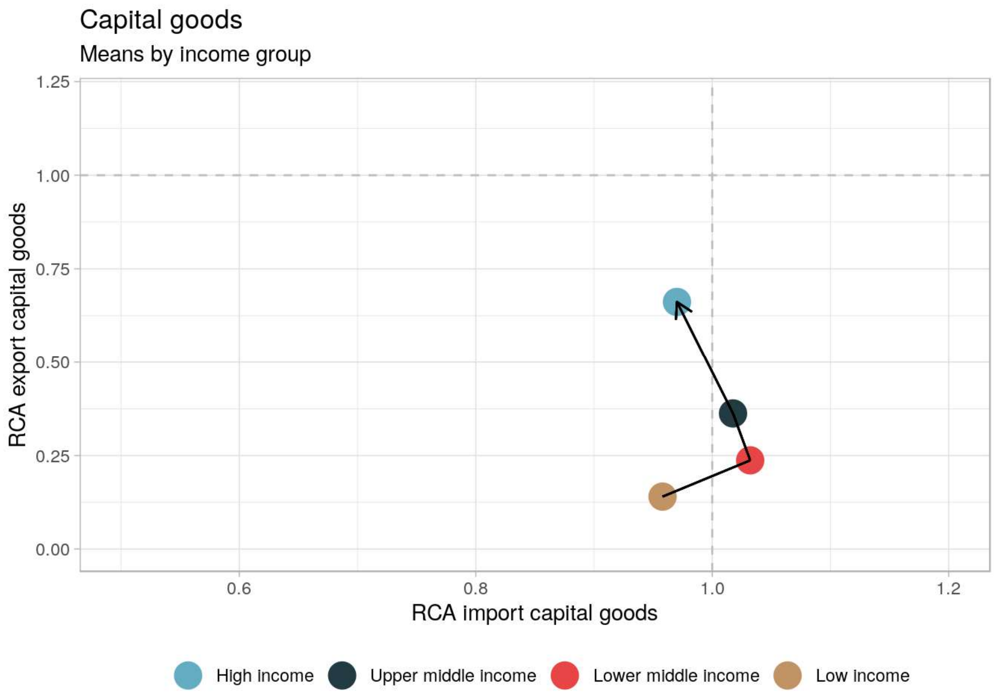


Figure 3.4: RCA exports and imports for capital goods by income group

For capital goods, which represent all types of production technology, this means that the higher a country's income, the more likely it is to be an exporter of such goods. Only a relatively small fraction of countries are specialized exporters, but around half of the countries are specialized importers and thus users of capital goods (for more details, see Appendix I).

Disclaimer for classification

Please note that this analysis provides a simplified means to analyse an otherwise very complex topic and any classification of a particular country and year should always be considered with a grain of salt: solid knowledge of the country's unique situation as well as the time profile of the RCAs is recommended. This is based on the following reasons:

- 'Revealed' trade patterns are used to infer adoption rates. Some countries, such as the United States, have a large domestic market. Their share of exports of high-technology goods in their total exports might be relatively small, although the U.S. can clearly be considered a technology leader.
- The cut-off at '1' tells a clear story in that it represents the world average of import or export shares; however, some countries might come very close to that cut-off, being

above 1 one year but below 1 in the next. Small product groups, in particular, might reveal high volatility (fluctuations), possibly resulting in a misleading story.

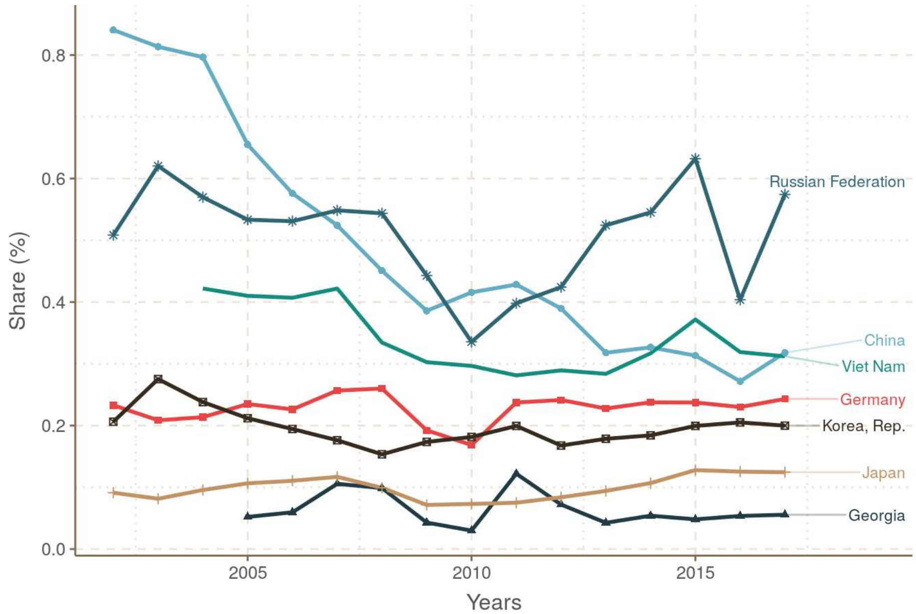
- To obtain a complete picture, the entire time series of a country must be looked at and other available country-specific information should be taken into account. In our example, China and Viet Nam changed groups over the years, which reveals some important information about their development.

The calculation of RCAs can alternatively be based on imports and exports as the shares of nominal gross domestic product. This variant leads to very similar results as those presented above. Also, using ‘1’ as the relevant cut-off to define the classification can be replaced by using the average of all countries’ RCA imports and exports, respectively. **We propose using ‘1’ as the cut-off as it is simpler and does not change the main insights discussed above when using the averages instead.**

3.2 Adoption of Industry 4.0 technologies

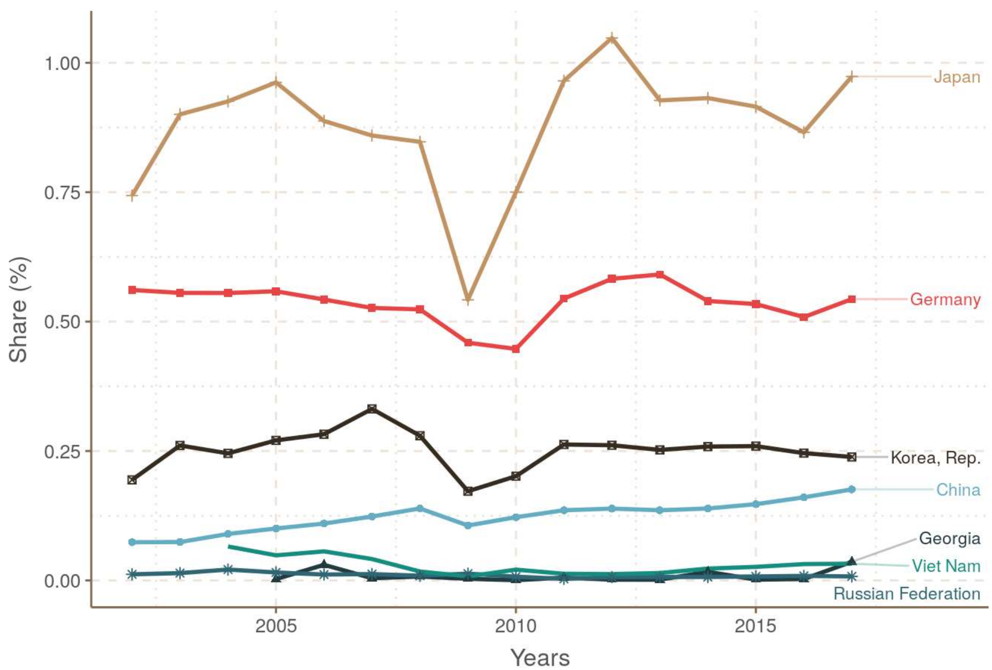
While the numbers above included all capital goods, the focus now switches to 4.0 goods, goods related to additive manufacturing, CAD-CAM or robotics. Using the same method as above, we can determine which countries are users and producers of goods manufactured using the latest technological production processes. The following graph (Figure 3.5) presents the percentage share of imports of 4.0 goods in total imports (indicator 3.5). The numbers for some of the countries in the subsample are remarkably stable over time but are still relatively low in absolute terms, as industry 4.0 is a relatively new phenomenon. Other research (see e.g., UNIDO (2020) or Gal et al. (2019)) shows that a small number of mostly highly productive firms are the first to adopt new technologies, creating a ‘digital capability gap’ among countries between the ‘best and the rest’.

During the first decade of the century, the Russian Federation, China and Viet Nam’s share of imports of 4.0 goods decreased. With the exception of China, the rest of the subset’s relative share of 4.0 goods imports has been increasing, albeit very slowly, since 2010. The Russian Federation reached its 2002 level again in 2017, with slightly less than 0.6 per cent imports of 4.0 goods. As with capital goods, the import shares of 4.0 goods do not at first glance seem to be related to income levels, at least not for our subsample of countries.



Source: UN COMTRADE

Figure 3.5: Share of 4.0 goods imports in total imports



Source: UN COMTRADE

Figure 3.6: Share of 4.0 goods exports in total exports

As regards the exports of 4.0 goods (indicator 2.6), there seems to be a correlation with income for our subset. Japan, Germany and the Republic of Korea are the largest exporters in terms of export shares.

As a benchmark exercise and to interpret the shares, the following presents the revealed comparative advantage for 4.0 goods (indicators 2.7 and 2.8). Numbers above 1 indicate imports or exports above the world average.

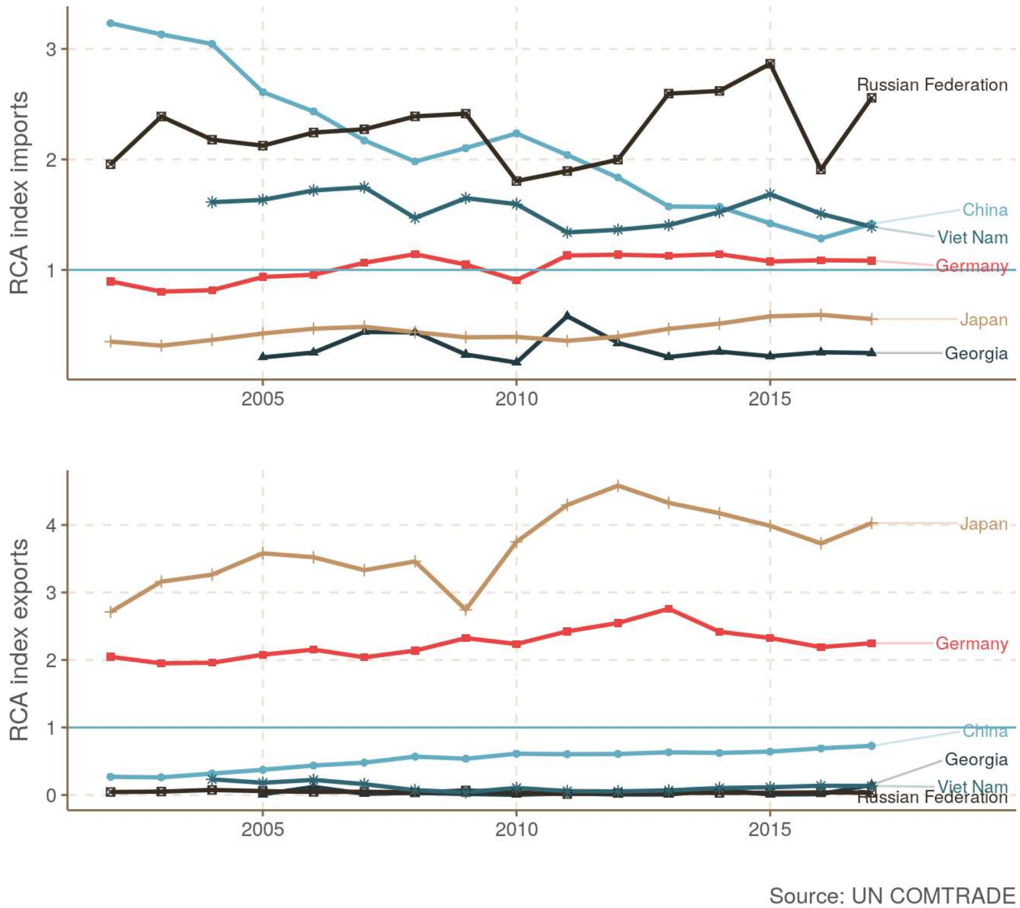


Figure 3.7: Revealed comparative advantage, imports and exports of 4.0 goods

This figure shows that some countries do not yet import capital goods or 4.0 goods, while others import Industry 4.0 technology but are not yet in a leading position in these technologies, which would allow them to also actively engage in exporting. Some others are in the process of adopting these technologies, and another group—in this case Japan—are technology leaders and main exporters of 4.0 goods. This analysis can be generalized for all countries, delivering the following picture:

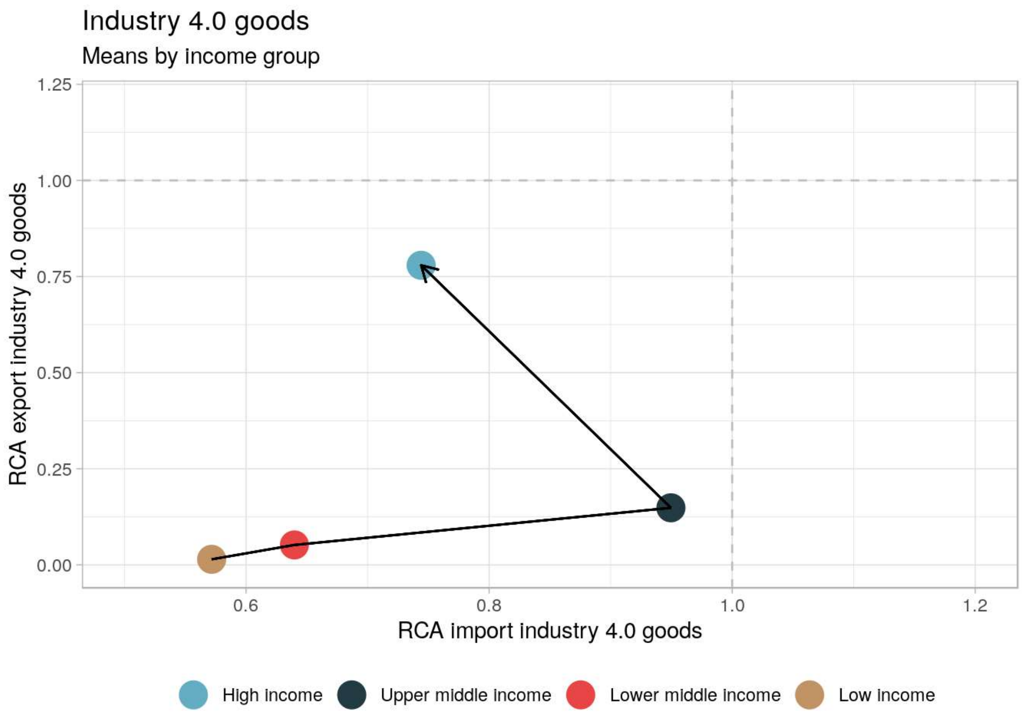


Figure 3.8: RCA exports and imports of Industry 4.0 goods by income group

Figure 3.8 illustrates the differences across income groups, which seem much more pronounced. While lower income countries only rarely import Industry 4.0 goods, the RCA imports of upper middle-income countries is by far the highest while their RCA exports are only slightly higher than that of lower income countries. In other words, upper middle-income countries are the countries that predominantly import Industry 4.0 technologies. High-income countries, on the other hand, are much more balanced. It should be noted, however, that a small and export-led sub-group of countries (see A) exists among the group of high-income countries, which are mainly responsible for driving up high-income countries' average RCA export share. There is hence evidence that the progression dynamics of Industry 4.0 goods are currently unfolding within the high-income country group while this is much more evident for capital goods across all income groups.

These initial indicators provide policymakers with an overview of their country and a comparison with others on where they stand in terms of overall technology adoption and absorption by looking at the trade patterns of both capital goods and 4.0 goods.

While Figure 3.4 and 3.8 provide some interesting insights on the evolution of classification patterns of the different income groups over time, further empirical evidence of technological progression can be derived, which is reflected in changes in the import/export structure of capital and industry 4.0 goods as economies grow richer. An additional discussion on this aspect is provided in Appendix I.

3.3 Adoption dynamics within Industry 4.0 goods

The analysis above indicates that Japan, for example, has a high amount of exports in both groups of goods. To determine whether Japan's success as an exporter is based on a single technology or is more evenly spread, we distinguish between different goods. As already discussed, 4.0 goods can be differentiated into additive manufacturing, CAD-CAM and (other) robotics. Figure 3.9 presents the share of a country's imports of Industry 4.0 goods (in per cent) in total imports.

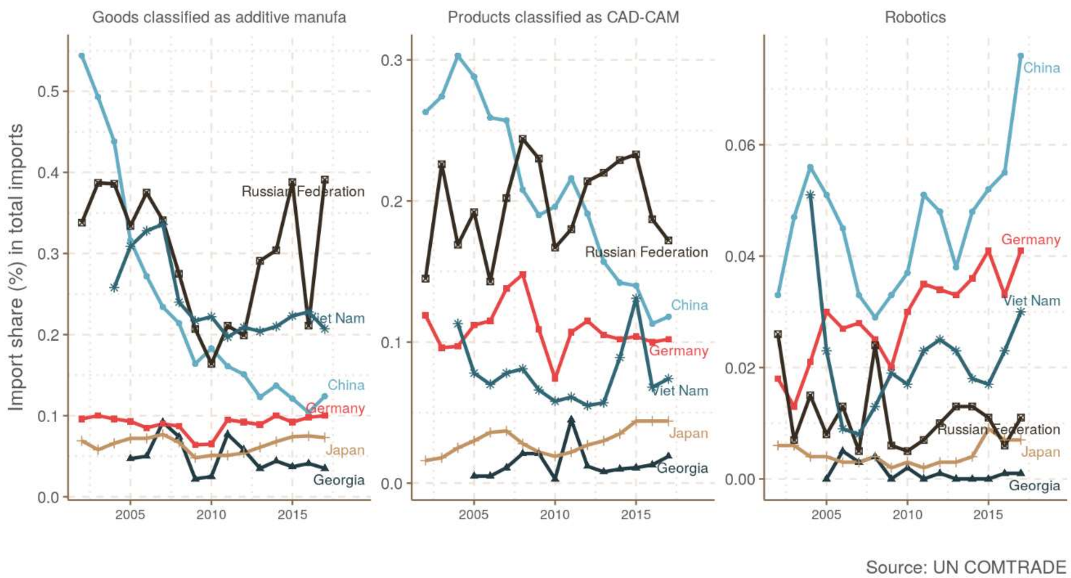


Figure 3.9: Share of 4.0 imports (%) in total imports

Our first observation is that import shares are very low across all countries with a maximum of around 0.4 per cent in 2017. This might not be surprising as these goods are among the newest generation of technological capital goods. However, countries in this subsample show an overall declining or stagnant share of imports of additive manufacturing or CAD-CAM. What is more, the relative position of countries in terms of the aggregate goods above did not change. This pattern does, however, change when we look at robotics: the share of robot imports in total imports are increasing for the most part.

ADOPTION SECTION SUMMARY

This section has provided a set of indicators that should be used together to fully understand technology adoption patterns. The share of imports that indicate the importance of a (group of) good(s) and their potential to contribute to the process of technology adoption are combined with the RCA of imports and exports to classify countries as users or producers. Disaggregating the data can reveal whether a country specializes in particular goods or technologies or whether it lacks some of these entirely. Additionally, the classification of countries together with their position in global income distribution can help policymakers compare their countries' revealed comparative advantage relative to others. This may highlight potential strengths and weaknesses in a country's adoption process and points to areas of potential policy interventions.

SUMMARY: How to use the concept

All indicators must be used jointly to obtain a complete picture of technology adoption with the help of trade data. To summarize:

1) Determine the import and export shares (indicators 2.1, 2.2, 2.5 and 2.6) of capital goods and 4.0 goods.

2) Calculate the revealed comparative advantage (RCA) of imports and exports of capital goods and 4.0 goods (indicators 2.3, 2.4, 2.7 and 2.8).

3) Plot RCAs over time (together with those of comparator countries).

4) Interpret the findings by considering changes over time and compare your country with the average of the same income group as a benchmark (compare Figures 3.4 and 3.8 or similar in Appendix I).

5) This analysis can be carried out for more detailed products or product groups to investigate whether the aggregate results are driven by specific goods in a particular country.

4. Robots and job losses in manufacturing

We will now shift our focus to robots. On the one hand, we can derive more detailed insights into one product group with increasing import shares (see Section 3.1.3). On the other hand, when jobs are at risk of automation, it is mostly robots that come to mind. As Mayer (2018) points out, the manufacturing sector is characterized by a number of routine jobs and therefore particularly exposed to the potential substitution of labour by robots.

It is important to note from the outset that different indicators have to be combined to properly evaluate the risk of job losses due to robotic automation. Generally speaking, we want to know (i) how many robots are already in use and how fast are they growing in numbers, (ii) how many workers are engaged in manufacturing and specifically in industries characterized as 'high risk industries'. Some countries are not included in the analysis due to their limited robot data set.

4.1 Robot intensity

Robot intensity measures the ratio of the number of robots relative to the number of employees (indicator 2.9). One disadvantage of this indicator is that its focus is limited to the dimension of robots alone, whereas previous indicators were based on a broader range of Industry 4.0 goods consisting of CAD-CAM, additive manufacturing and robots. Consequently, the results presented in this section should always be interpreted in the context of robotics and are therefore not necessarily representative of the wider range of Industry 4.0-related technologies or the wider adoption capabilities of any of the countries considered in this study.

As the 'smart factory' is mostly about intelligently connecting machines (robots) and other parts of the production process, the use of industrial robots is a first indicator of how relevant this issue is for countries or how prepared countries are in this respect. The intensity of robot use in the production process will be calculated as the stock of industrial robots per 1 million employees. If this ratio is increasing, it can be interpreted as a measure of progress of a country's industrial automation capacities.

Figure 4.1 presents robot intensity (indicator 2.9) over time. The vertical axis is displayed in log-form to display all countries in one graph.[19] The figure replicates the patterns from above. Industrialized countries, such as Japan, the Republic of Korea or Germany already use up to 80,000 robots per 1 million employees. On the other hand, in Viet Nam or the Russian Federation, less than 1,000 robots per million employees are being used. In total, with the exception of Japan, all selected countries reveal an increase in robot intensity over time.

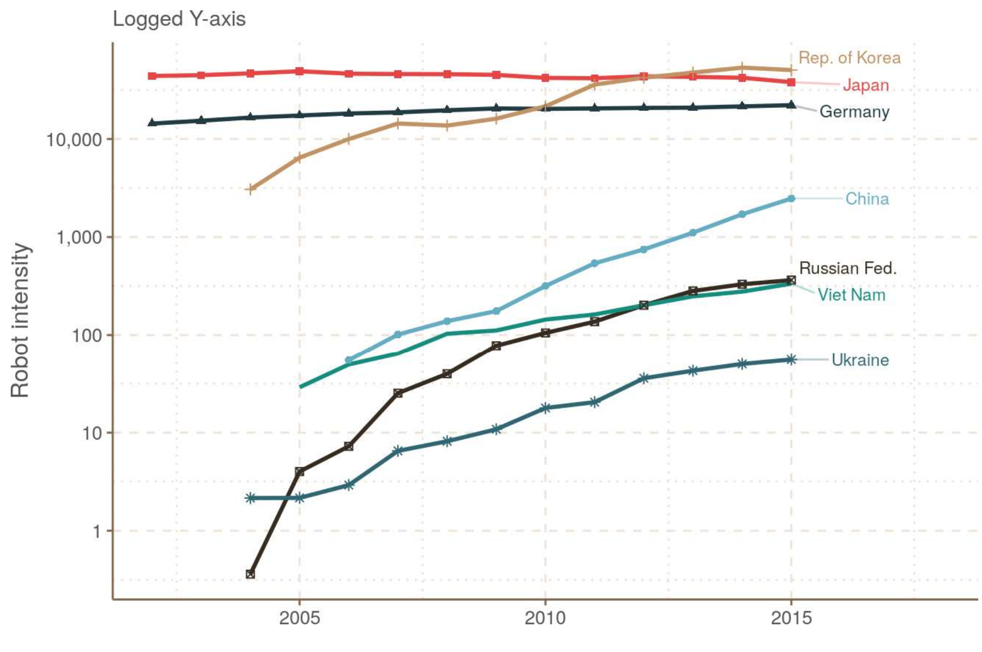
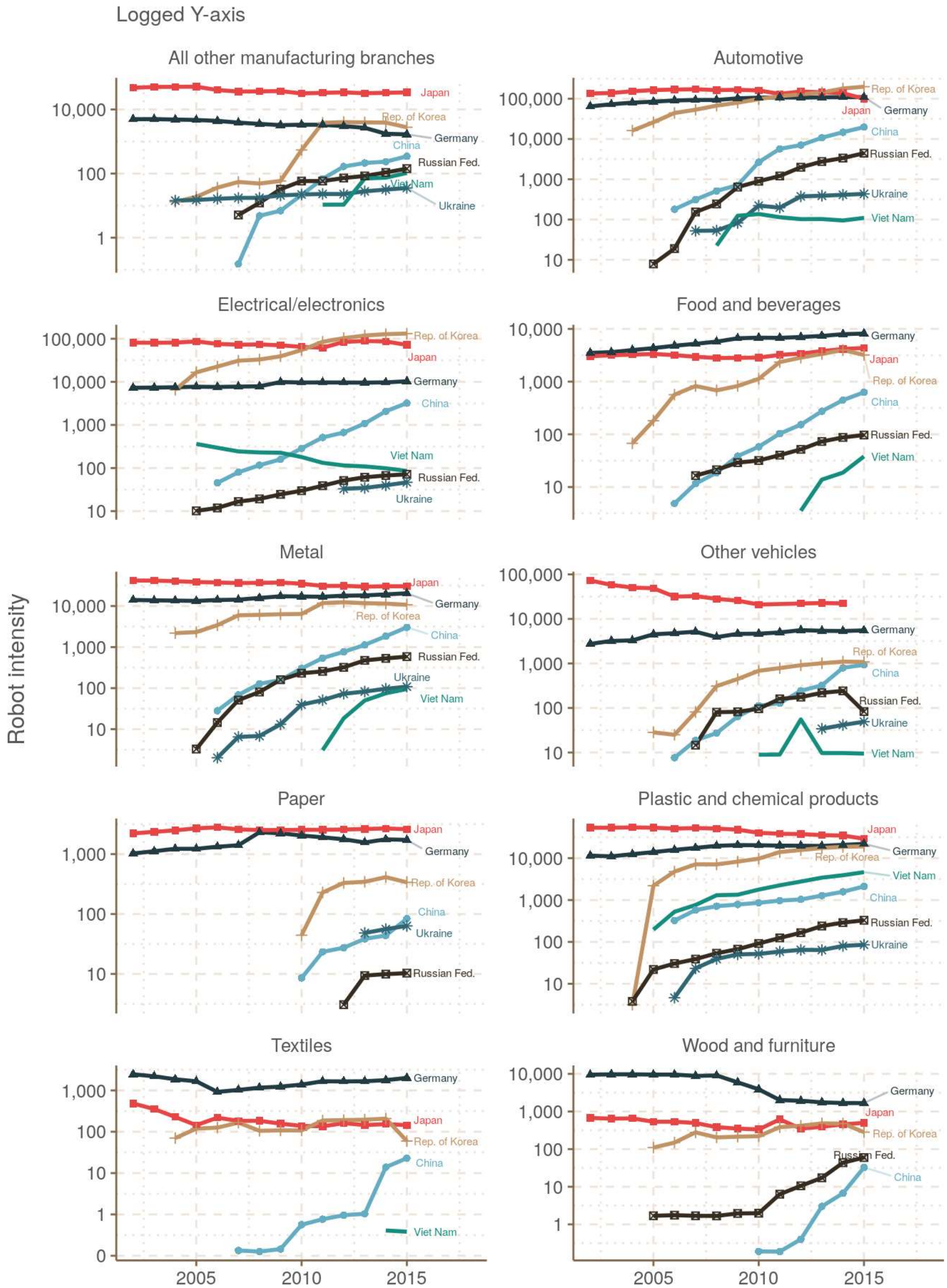


Figure 4.1: Robot intensity: robots per 1 m. manufacturing employees

This picture is remarkably stable when disaggregated by industry (Figure 4.2) to determine robot intensity by industry (indicator 2.10). Without exception, it is high-income countries that demonstrate higher robot intensity over time. Robot intensity also shows a large variation across industries, with the highest number of robots found in the electronics and automotive industries.



Source: IFR, INDSTAT 2 2019 ISIC rev3.

Figure 4.2: Robot intensity: robots per 1 m. manufacturing employees

4.2 Manufacturing jobs at risk of automation

Robot intensity increased over time in nearly all countries included in the analysis. Against this background, one important dimension of the discussion surrounding new technology are their potential benefits and risks. In the context of robots, it is the effect of robotic automation. Similarly to the employment composition analysis in EQuIP Tool 5: *Employment Composition*, manufacturing jobs at risk of automation can be quantified. This concept is particularly complex as automation itself is technology-biased and more likely to affect industries (and countries) with high capital intensity. This makes the issue of jobs at risk of automation a particularly multifaceted one that hinges on numerous factors. Three main components are discussed in the remainder of this section.

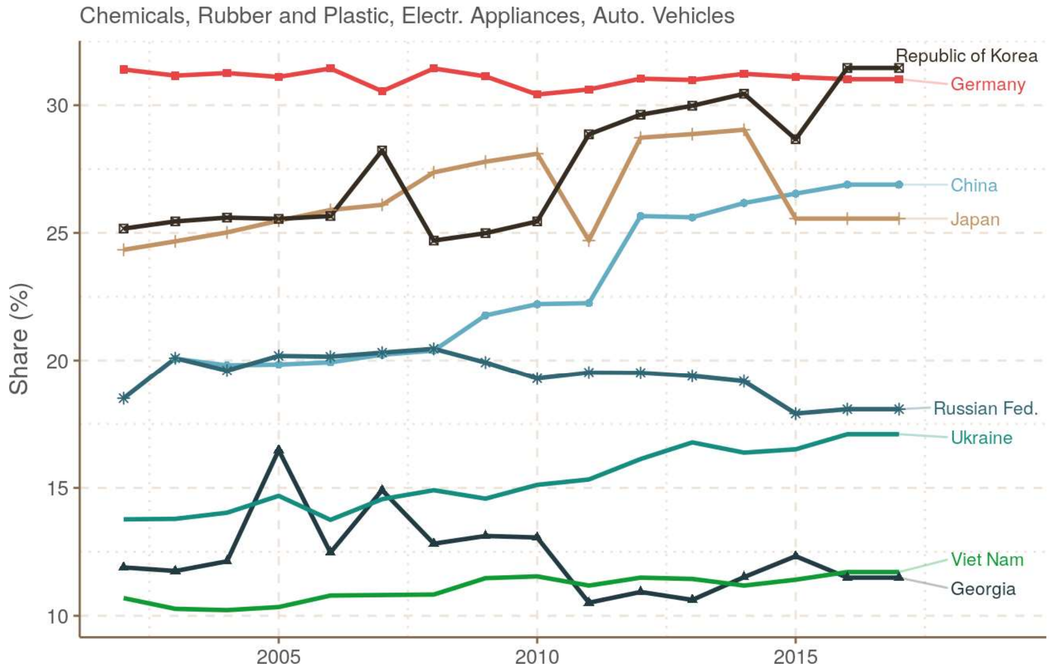
A recent study (Mayer 2018) identifies manufacturing share (indicator 2.12) as a first important variable in identifying jobs at risk from Industry 4.0. The argument is that the manufacturing sector is characterized by routine jobs and is therefore sensitive to robot/human capital substitution. Countries with a severely underdeveloped manufacturing sector and a high share of (non-industrialized) agriculture in the economy are not yet very likely to expect much automation-induced unemployment because of the emergence of improvements in production processes in medium- to high-technology industries.

Assuming a well-developed manufacturing basis, the effect of automation-induced unemployment further depends on the country's industrial composition. Mayer (2018) identifies a subset of manufacturing industries considered to be at a high risk of automation (see Table 4.1). As he points out, "job displacement by robots in relatively skill-intensive and well-paying manufacturing, such as the automotive and electronics sectors, is more profitable than in relatively labour intensive and low-paying sectors, such as apparel" (Mayer, 2018, p.10) and that "economic factors are more important for robot deployment than the technical possibilities of automating workers' tasks" (Mayer, 2018, p.11) . This set of industries might change over time when others become more skill intensive or if the technology evolves.

Table 4.1: Industries at risk of robotic automation, based on Mayer (2018)

ISIC Rev. 3 Industry Code	Name of Industry
24	Chemicals
25	Rubber and plastic
31	Electronic appliances
34A	Automobile vehicles

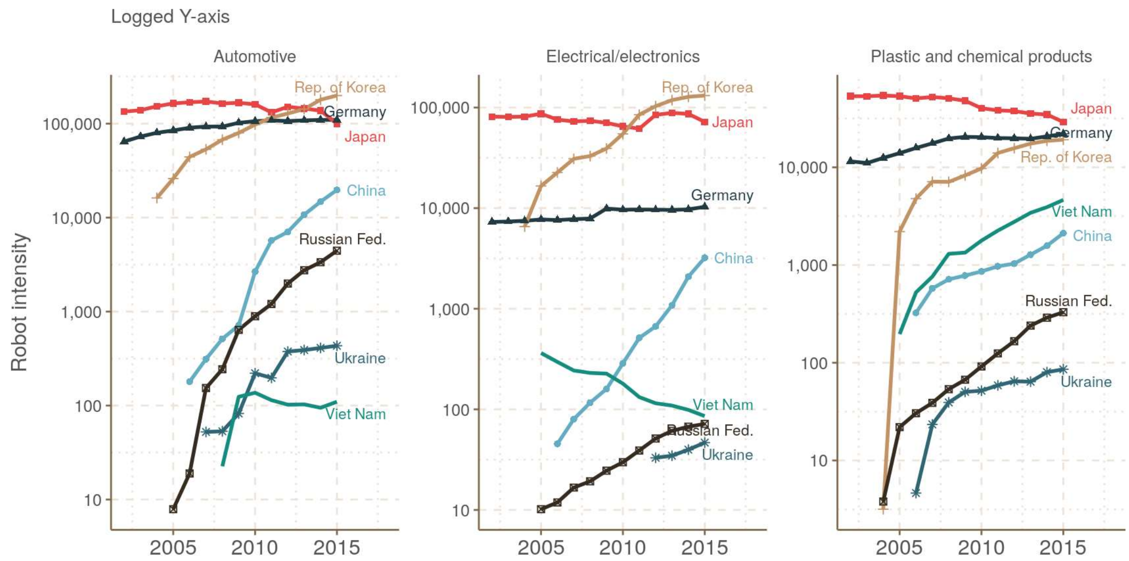
Applying this classification of high-risk industries to the country sample in this module, Figure 4.3 presents the share of workers in the chemicals, rubber and plastic, electrical appliances and automotive vehicles industries (indicator 2.11). It illustrates notably higher risks for the set of advanced economies in the sample (Germany, Japan and the Republic of Korea) while the trend in the Russian Federation, Viet Nam and Georgia is relatively low and stable over time. Given its dynamic growth and aspiration of becoming a technology leader, the trade-off between technological advancement and the risk of job losses due to Industry 4.0 is very evident in the case of China: within 10 years (between 2007 and 2017), the share of jobs at risk in China has increased by around 7 percentage points and is now closing in on the group of most advanced economies.



Source: INDSTAT 2 2019 ISIC rev3.

Figure 4.3: Share of jobs at risk of automation

Robots are used in different industries to different degrees. In 2016, two-thirds of robots in our country sample were being employed in automotive and electronics, which overlaps with the industries identified above. There is considerable variation across countries. Robot use in the production of cars is relatively intense in Germany compared to other industries. The use of robotic automation in the automotive industry of the Republic of Korea and Japan is even higher, and the production of electronics in these two countries is also very robot-intensive. Viet Nam, the Russian Federation and China use robots much less intensively, with China's robotic automation spread relatively evenly across industries while the Russian Federation's is more skewed towards automobiles and metals. Robot use in Viet Nam is higher in the production of plastic and chemical products.



Source: IFR, INDSTAT 2 2019 ISIC rev3.

Figure 4.4: Robot intensity: robots per 1 m. manufacturing jobs

As was the case in the previous section, the indicators must be combined to arrive at a preliminary conclusion whether jobs are at risk of robotic automation. We thus follow Mayer (2018) and look at a large sample of 111 countries to determine whether we can identify a more general pattern. Figure 4.5 relates the average (2002-2016) risk industry employment (indicator 2.11) to total manufacturing employment (indicator 2.12). We furthermore distinguish countries by income group and by their average robot intensity (size of points, indicator 2.9).

The graph can be divided into 4 quadrants. The top-left quadrant includes countries in which employment in risk industries is relatively overrepresented. For example, in Mexico 5 per cent of all employees work in manufacturing industries. However, of those, over 30 per cent are employed in risk industries. Countries in the top-right quadrant have a high number of manufacturing employees overall and in risk industries as well. In large parts, these are high-income and upper-income countries that already have intensive robot use (size of symbol). In general, the larger a country's manufacturing sector and the higher the number of employees who work in 'risk industries', the higher the risk of job losses.

Grouping countries by income, we find that employees in developed as well as in upper middle-income countries are, on average, more exposed to risk of job losses due to automation, while least developed countries are not (yet) strongly exposed to such risk. Moreover, high-income countries have higher robot intensity, confirming previous findings.

These conclusions, however, pose a challenging conundrum: on the one hand, they suggest that robotic automation will not invalidate the important role of industrial development for less-developed economies per se; on the other hand, the fact that the use of robots is positively correlated with more high-skilled industries may pose an even greater challenge for less-developed countries with regard to sectoral upgrading. That is, countries that want to increase their share of high-technology industries, at least temporarily, will be exposed to the risk of some job losses due to automation.

Figure 4.5: Jobs at risk of robotic automation

This last observation brings us to the third factor that plays a crucial role in manufacturing job losses at risk, namely the (non-) maturity of a country's automation tendencies. Is robot intensity growing rapidly or has it reached some saturation? This dimension can be analysed by comparing the growth of a country's robot intensity with the overall level of robot intensity (indicator 2.9).

For countries with low growth rates, the actual risk of job losses due to automation is relatively low, even though this particular risk may remain high as a consequence of technological advancements. This takes these jobs out of the 'danger zone' where technological advancements may result in involuntary job losses, at least in the short term. Conversely, countries that have not yet reached this stage of maturity may face a high risk of job loss due to robotic automation if they show a high growth rate in robot intensity as well as a steady increase in their stock over time.[20]

As Figure 4.5 reveals, Mayer's findings (2018) suggest that countries characterized by a manufacturing sector tilted towards electronics, automotive and chemical industries are more vulnerable to job displacement because it is more profitable. A higher risk of job displacement could be associated with higher robot intensity because countries that have already adopted more extensive robot technology are also more inclined to continue with their robotization efforts because they have already acquired all the necessary capabilities. This process is only expected to continue, however, until countries reach a certain level of maturity in robotization. Thereafter, it is unlikely that countries will continue to inject robots into the production system, and they will instead try to upgrade towards higher generations of Industry 4.0 goods, including artificial intelligence, big data and CAD-CAM. The risk of job displacement in emerging countries may be more apparent.

Figure 4.6 shows the annual (2002-2015) growth rate of robot intensity (growth rate of indicator 2.9) on the Y-axis and robot intensity (indicator 2.9) on the X-axis. Technology leaders, such as Germany and Japan, can be described as having reached a degree of maturity with a high yet very static degree of robot intensity over time. Robot intensity still seems to be expanding in the Republic of Korea despite the country leading the pack already in 2014. Compared to the Russian Federation, Viet Nam and China seem to be expanding their relative stock of robots, albeit from a low level. This picture (as many others in this tool) can potentially change dramatically as new technology becomes available.[21]

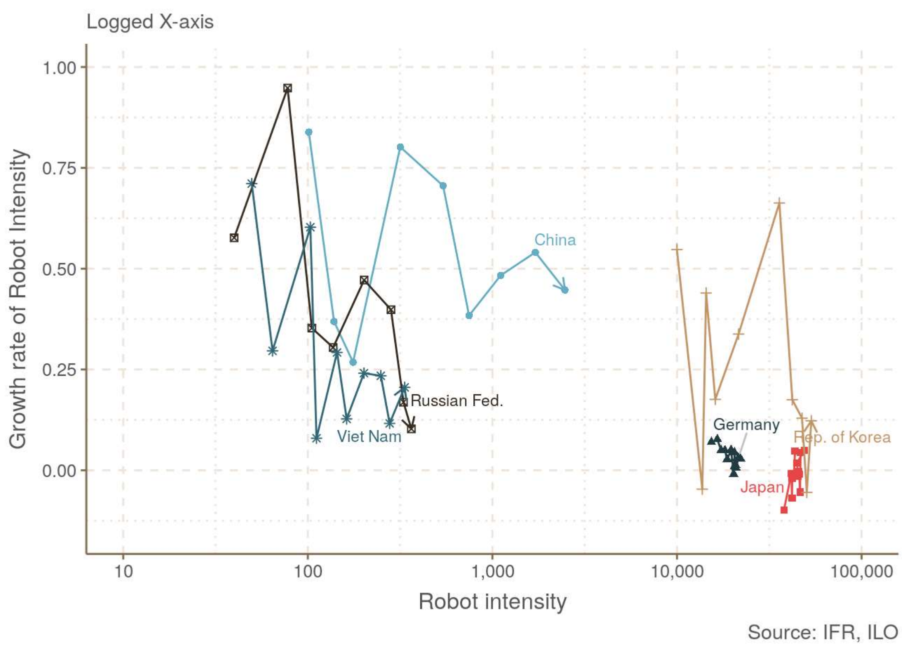


Figure 4.6: Maturity effect of automation

ROBOTS SECTION SUMMARY

This section has shown that different indicators must be combined to obtain a coherent picture of automation processes. Although some industries may show a higher likelihood of replacing jobs with robots, the stage (maturity) of robotization the manufacturing sector has already reached is also of relevance. If a country's goal is to increase the degree of automation in the production process, it might initially be exposed to the risk of job loss due to robotic automation, especially in mid- to high-technology sectors. Once a certain level of maturity has been reached in the adoption of robots, the risk decreases again. Policymakers must be aware of the potential need to ease the transition for workers during upgrading.

5. Productivity

This section links the current debate on the technological revolution due to the emergence of smart digital technology to macroeconomic indicators across manufacturing industries. The indicators presented in the following section allow us to analyse the differences in the dynamics of manufacturing industries' productivity, value added and employment growth over time. A straightforward way of analysing and comparing country-specific industry profiles across aggregates over time is proposed as well, as is a simple forward-looking approach to identify the direction in which a given manufacturing industry is developing.

As discussed earlier, the concept of *runner industries* emphasizes the notion of sustained employment growth, a feature that cannot be overstated in light of the jobs at risk of automation discussed in the context of newly emerging technologies with smart systems and robots. The instrument of runner industries is also extended to that of *runner industry exposure* which represents a straightforward way to characterize the share of industries within the manufacturing sector that feature positive productivity and employment characteristics. In other words, it quantifies the share of value added and employment of a country's manufacturing sector that can be attributed to the set of respective runner industries.

The subsequent section presents a case study of runner industries analysis for Viet Nam and Morocco and illustrates how policy analysts can utilize the proposed instruments to capture industry-level dynamics.

5.1 Runner industries

The first step in the empirical analysis entails the identification of *runner industries*. Particularly through the adoption of new technologies **it is very important to recognise industries with positive value added, employment and productivity growth.** This set of industries has remained at the forefront of value added and employment generation and therefore stands in stark contrast to the jobless or declining growth types discussed earlier (see Figure 1.5).

To identify these industries quantitatively, the compound annual growth rates ($CAGR$) for value added, employment as well as productivity are calculated as follows:

- Retrieve data (see Table 2.14):
  - Obtain value added and employment data from INDSTAT.
  - Obtain population data from an alternative data source such as the World Development Indicators.
- Calculate series:
  - Calculate value added per capita as well as employment-population ratio.[22]
  - Any potential price effects in the series must be eliminated for the value added series (see Appendix E for more details).
  - Calculate productivity[23] series as follows:

$$Productivity = \frac{Value\ added\ per\ capita}{Employent\ population\ ratio}$$

- Calculate compound annual growth rates (CAGR) for each of the three variables:
  - $CAGR = \frac{End\ value}{Initial\ value}^{\frac{1}{no.\ of\ years}} - 1$

- Calculate the averages of the CAGRs of value added, employment and productivity for the aggregates of interest. In our case, that would be:
  - Global runners - the three growth rates for all available countries are calculated to determine an average of these growth rates across all countries for all respective industries;
  - Income group runners - the three growth rates for all available countries that belong to the same income group(s) are calculated to determine an average of these growth rates across all countries for all respective industries. A set of lower middle-income countries, namely Viet Nam and Morocco, is used in our case study;[24]
  - The runners for Viet Nam and Morocco exclusively.
  - The time period for which the runner industries are identified may vary and lies within the discretion of the policy analyst. We will discuss this point in greater detail throughout the remainder of this section.

The indicators obtained through this procedure represent the basis of our subsequent analysis. Table 5.1 summarizes the results for the global runner sample. The food and beverages, rubber and plastic as well as fabricated metals, electrical machinery and motor vehicles industries are found to have positive employment and productivity growth over the full data sample from 1963 to 2017.

Table 5.1: Runner industries: Global runners for the full sample period

Manufacturing Industries	Productivity CAGR	VA CAGR	Employment CAGR	Global Runner
15: Food and beverages	0.76	1.15	0.12	Yes
16: Tobacco	1.02	-1.91	-3.28	
17: Textiles	1.60	-2.43	-4.19	
18A: Wearing apparel	0.74	-1.75	-2.76	
20: Wood products	0.53	-0.10	-0.83	
21: Paper	2.25	1.52	-0.89	
22: Printing and publishing	2.24	0.39	-1.89	
23: Coke and refined petroleum	0.14	-0.82	-0.94	
24: Chemicals	2.67	2.64	-0.19	
25: Rubber and plastic	1.03	2.24	0.96	Yes
26: Minerals	1.84	1.07	-0.94	
27: Basic metals	1.57	0.26	-1.49	
28: Fabricated metals	1.22	1.71	0.32	Yes
29C: Machinery	3.36	3.26	-0.40	
31A: Electrical machinery	0.37	3.32	1.55	Yes
33: Precision instruments	4.36	3.81	-0.56	
34A: Motor vehicles	1.45	2.91	1.25	Yes
36: Furniture, n.e.c	-0.06	0.59	-0.46	

Note: INDSTAT 2 rev.3, 1963-2017.

By conducting the runner industry analysis, we can learn more about the general trends and dynamics within manufacturing. This approach also has its limitations, however: first of all, it analyses productivity growth over an extensive period of time. At the same time, it creates averages across many countries, some of which may only have data for earlier or later periods. In this sense, this initial analysis measures the effect of colour TVs in the 1970s, for example, together with the digital revolution and Industry 4.0. This can be both instructive but also misleading, as developing countries, in particular, have much better data coverage for the most recent decades.

Consequently, if one wanted to learn more about runner industry trends in the more recent past, say, since 2000, a similar table can be obtained by simply truncating the data. The results are presented in Table 5.2 and show that positive growth dynamics can now be reported for more manufacturing industries: compared to the table above, the chemicals and precision instruments industries can now be classified as runner industries. Please note that this difference in patterns, which is the result of changing the time period considered, is an important feature of the runner industry concept (see Appendix C for more details).

Table 5.2: Runner industries: Global runners for the post-2000 sample period.

Manufacturing Industries	Productivity CAGR	VA CAGR	Employment CAGR	Global Runner
15: Food and beverages	0.39	1.07	0.46	Yes
16: Tobacco	1.50	-1.63	-3.68	
17: Textiles	1.19	-2.72	-4.18	
18A: Wearing apparel	-0.03	-2.29	-2.57	
20: Wood products	0.16	-0.56	-0.93	
21: Paper	1.29	0.65	-0.75	
22: Printing and publishing	2.68	-0.51	-3.30	
23: Coke and refined petroleum	-1.74	-2.06	-0.23	
24: Chemicals	2.05	2.46	0.15	Yes
25: Rubber and plastic	0.90	2.03	1.06	Yes
26: Minerals	1.13	0.99	-0.68	
27: Basic metals	0.30	-0.51	-1.11	
28: Fabricated metals	0.31	1.37	0.75	Yes
29C: Machinery	3.32	3.39	-1.55	
31A: Electrical machinery	1.14	3.96	1.35	Yes
33: Precision instruments	3.15	4.86	0.97	Yes
34A: Motor vehicles	1.36	2.90	1.64	Yes
36: Furniture, n.e.c	-0.20	0.13	0.26	

Note: INDSTAT 2 rev.3, 2000-2017.

It is also important to note that the results discussed so far are only reflective of the global average and hence present the pooled experience across a very broad and heterogeneous set of countries, both in the developing and developed world. Since the very heterogeneous diffusion patterns of new digital technology clearly crystallized in the previous sections, it is also highly recommended to conduct the same runner industry identification for a more narrowly defined group of countries. A natural candidate for this more granular analysis is a set of countries that belongs to the same income group (the so-called 'income group' runners). The same argument can also be invoked for conducting a runner analysis at the country level (also referred to as country-level runners). This makes it possible to closely follow country-level differences in industry performance profiles. This dimension is used for a more granular look at country-level heterogeneities in the section on 'Advanced manufacturing industry profiling'.

A condensed summary of all classified runner industries across the different specifications is presented in Table 5.3.[25] This table demonstrates that there are a great number of runner industries in lower income countries in the post-2000s, where positive employment and productivity growth have been achieved despite the most recent technological developments. Table 5.3 also shows that runner industries are typically identified to be part of the medium- and high-technology group which are characterized by their higher propensity to engage in R&D (OECD 2011). It is important to note that the identification of runner industries is not the result of some fixed classification (as is the case for technology groups, for example), but is the direct result of the growth dynamics of value added and employment: if an industry has positive growth dynamics, it will also qualify as a runner industry. This is evident in the food and beverages industry which, despite being considered a low-technology industry, also belongs to the set of runner industries in the majority of observed cases. The latter is an important insight on future development as well: it is possible for a low-technology industry to become more technologically sophisticated in the future on account of new technologies. If this goes hand-in-hand with an expansion of the industry (through value added and employment growth), it can be identified as a runner industry. In this sense, the runner industry classification can detect such dynamism as well, which can be referred to as intra-industry upgrading (see Appendix G for more information).

Looking at Table 5.3, it also makes sense to link the results back to the earlier discussion on new digital technology and high-technology industries:

- The first observation is that runner industries seem to be dominated by medium-/high-technology industries: following OECD (2011), the medium-/high-technology industries, chemicals, electrical machinery, precision instruments and motor vehicles appear very robustly across the different aggregates.
- What is more, the high-risk industries (Mayer 2018) that were identified earlier (electrical machinery, motor vehicles, chemicals and rubber and plastic) are also represented here.

This overlap is both striking but also not very surprising: industries with high R&D investment are by and large at the forefront of the current digital revolution in manufacturing. This might rightfully raise the question to what degree jobs in these industries are at risk of being replaced by new and smart robots. At the same time, these R&D-intensive industries have also been leaders in previous automation efforts in the past. Was this at the expense of jobs? As our runner analysis has just demonstrated, it is precisely these industries that can be characterized by a positive growth in productivity, value added *and* employment. It is essentially this set of industries that has had an influential effect on manufacturing: job loss and job creation are central elements of the modernization process of manufacturing industries.

Lastly, Table 5.3 also reveals that the runner profile for Viet Nam (as well as Morocco) differs considerably to that of its lower middle-income peers. At first glance, it appears that Viet Nam reports more runner industries for the low(er)-skilled manufacturing industries while the high(er)-skilled industries do not seem to qualify as runners. We will explore these differences in greater detail in the next section.

Table 5.3: Summary of runner industries classification by aggregate

	Global runner		Country-level runner		Income group runner	
Manufacturing Industries	Full sample	Post-2000	Viet Nam runners	Morocco runners	Full sample	Post-2000
15: Food and beverages	x	x	x	x		x
18A: Wearing apparel			x			
21: Paper			x			
22: Printing and publishing				x		
24: Chemicals		x		x	x	x
25: Rubber and plastic	x	x	x	x		
26: Minerals						
27: Basic metals			x	x		
28: Fabricated metals	x	x	x	x	x	x
31A: Electrical machinery	x	x			x	x
29C: Machinery				x		
33: Precision instruments		x		X		
34A: Motor vehicles	x	x	x		x	x
36: Furniture, n.e.c		x			x	x

Note: INDSTAT 2 rev.3. The income group is lower middle income and low income countries

5.2 Advanced manufacturing industry profiling

As emphasized above, the notion of runner industries is not a static concept. It depends fundamentally on the set of countries and time periods investigated. In other words, just because one industry shows declining global growth does not imply that this will have a negative value added and employment growth dynamics for all countries and regions. In the same vein, the observation that another industry has recorded inclusive and tenable growth across the majority of countries in the same income group does not imply that this industry must be equally successful for all countries in that group. In this regard, it may not be a sensible strategy for a developing country to identify and/or pursue the development of runner industries identified either on the global stage or, more specifically, in a subset of advanced economies.

Consequently, for a more in-depth analysis with a focus on the cross-sectional differences between countries and aggregates, it makes sense to summarize the growth rates of value added, employment and productivity in one table (Table 5.4). Whereas the wearing apparel industry in lower income countries has been affected by increasing jobless growth, it qualifies as a runner industry in Viet Nam. In Morocco, on the other hand, the wearing apparel industry is characterized by declining growth, despite the fact that it has registered positive productivity growth. In other words, our analysis indicates that the Vietnamese and Moroccan wearing apparel industries have followed a very different trajectory to that of the global average and/or that of its lower middle-income counterparts; they also differ significantly from one another.

Table 5.4: Viet Nam and Morocco vs. lower income countries, full sample period

	Morocco			Viet Nam			Lower income countries		
Manufacturing industry	Productivity CAGR	VA CAGR	Employment CAGR	Productivity CAGR	VA CAGR	Employment CAGR	Productivity CAGR	VA CAGR	Employment CAGR
15: Food and beverages	-2.28	1.14	3.51	1.92	3.71	1.76	1.88	1.83	-0.19
16: Tobacco	5.25	0.27	-4.74	-3.86	-5.87	-2.09	3.82	0.94	-2.72
17: Textiles	3.07	0.28	-2.71	-2.80	0.17	3.05	0.39	-2.15	-2.85
18A: Wearing apparel	1.09	-1.17	-2.23	2.57	9.99	7.24	3.67	3.40	-0.47
20: Wood products	-0.85	-0.60	0.25	NA	NA	NA	0.91	-0.83	-1.68
21: Paper	6.55	3.90	-2.48	3.58	7.42	3.71	2.96	4.06	-0.51
22: Printing and publishing	0.59	1.89	0.36	NA	NA	NA	1.51	0.34	-1.77
23: Coke and refined petroleum	-0.15	-0.18	-0.03	NA	NA	NA	1.28	0.24	-1.02
24: Chemicals	3.20	3.27	0.07	-0.48	5.27	5.77	1.53	2.44	0.78
25: Rubber and plastic	0.16	1.43	1.28	-1.08	6.62	7.78	-0.06	3.00	2.19
26: Minerals	5.21	5.47	0.24	-0.67	0.07	0.74	2.32	2.23	-0.45
27: Basic metals	7.63	10.90	3.04	8.61	15.08	5.96	3.38	2.58	-0.73
28: Fabricated metals	1.45	2.01	0.56	-5.24	0.49	6.04	2.40	2.11	0.01
29C: Machinery	0.35	1.15	0.80	NA	NA	NA	0.31	-1.61	-3.31
31A: Electrical machinery	-5.96	-0.77	5.52	NA	NA	NA	0.80	3.84	4.82
33: Precision instruments	5.20	10.89	5.41	NA	NA	NA	10.88	4.19	-5.62
34A: Motor vehicles	-5.60	0.44	6.40	4.50	9.50	4.78	2.11	4.57	2.68
36: Furniture, n.e.c	NA	NA	NA	-5.59	-0.64	5.24	0.85	1.52	1.11

Note: INDSTAT 2 rev.3, 1963-2017. Results based on lower income country group aggregate.

Table 5.4 also allows us to investigate why the medium-/high-technology industries electrical machinery and precision instruments are not identified as runner industries for Viet Nam while they are income group runners: there is no data available for these industries from Viet Nam. While this is certainly discouraging, it does not mean that the analysis must end there: examining the Vietnamese raw data reveals that no Index of Industrial Production (IIP) data are available, a variable that is required to calculate the real value added series see (**Box 5.1** for more information). For a more detailed explanation on overall data availability, see Appendix E.

BOX 5.1: Recommendation on the use of IIP series in case of limited data coverage

In some cases, it is not possible to derive meaningful statistics due to the lack of data. For example, if either value added or employment data is missing for a significant set of industries, a runner industry analysis is not feasible. In other cases, the Index of Industrial Production (IIP) necessary to deflate the nominal value added series is missing (see Appendix E on deflation for more information) for the country cases analysed in this tool.

If this is the case, it is recommended to check whether the IIP series for the entire manufacturing aggregate is available. If so, the manufacturing sector IIP series can be used instead to deflate the nominal value added series for a particular industry. It should be noted that in this case, it is assumed that the inflation dynamics of the entire manufacturing sector are similar to that of the given industry of interest. While this may not necessarily be fully reflective of the actual industry level dynamics, it allows for a more comprehensive analysis of the industry dynamics within manufacturing, which would have otherwise been impossible. In any case, analysts should always specify whether they have used this 'second best' approach in their analysis to deflate the value added series.

So far, we have identified the differences between Viet Nam and Morocco's runner industries and those of the average lower income country (income group runner). Next, we turn to the differences in growth performance between Viet Nam and **all other lower income countries**. The differences are illustrated in Figure 5.1, which shows a simple histogram for the productivity, value added and employment CAGRs: this visual tool is helpful in illustrating how different the growth rates across the set of countries included in the analysis are.

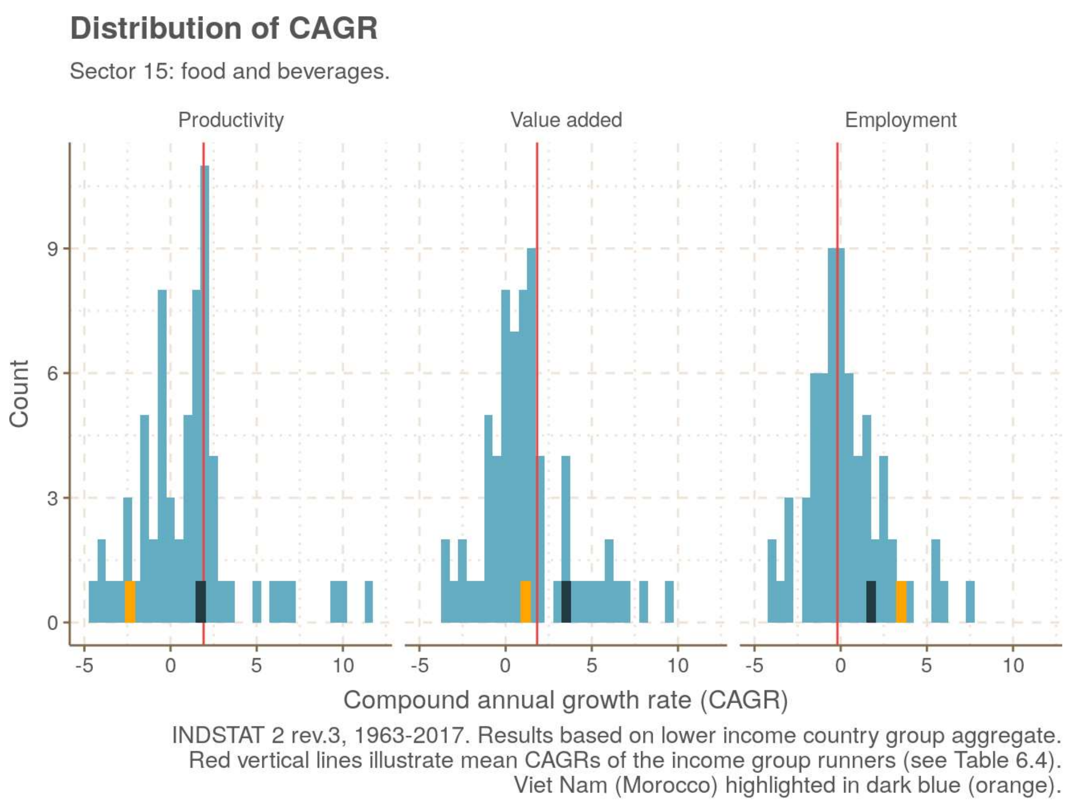


Figure 5.1: CAGR distribution food and beverages

The red vertical lines represent the average growth rates for each of the three variables. The three CAGRs for Viet Nam are denoted in dark blue and in orange for Morocco. This illustration serves two main purposes: first of all, it allows us to examine whether the average growth rates are driven by some extreme (either very high or very low) growth rate or whether they are representative of sector dynamics.[26] In the case presented here, the histogram seems to be slightly positively skewed. This means that the right tail of the distribution (the right side of the histogram) is longer (has more higher values) than the left side.[27] In other words, a few countries report considerably higher growth rates for productivity, value added and employment. At the same time, the highest number of countries report productivity (value added) growth rates of roughly +2 (+1) per cent and -0.5 per cent for employment as illustrated by the peak of the histogram count. Secondly, by comparing the histogram and the average with the recorded growth rates for Viet Nam (dark blue bar in Figure 5.1), we can easily and quickly compare Viet Nam's growth performance with that of other countries: while Viet Nam's productivity growth rate appears to be in line with that of the majority of economies examined here, its value added and employment growth rates are among the highest in the sample. This result again illustrates the importance of considering productivity dynamics alongside its components, as a similar productivity growth rate could have also been achieved by a lower value added and potentially negative employment growth rate as is the case of the lower middle-income countries (Table 5.4). As for Morocco, Figure 5.1 illustrates that the country's food and beverages industry has a value added growth rate similar to the average, while it also has one of the highest employment growth rates of all lower middle-income countries. Average value added growth coupled with above average employment growth explains why Morocco's labour productivity is among the lowest of all lower middle-income countries considered in our analysis.

5.3 Runner industry exposure

The previous section discussed ways to measure the performance of manufacturing industries by delineating productivity, value added and employment. We explained why this type of analysis is a sensible choice for country comparators and time dimensions. We also highlighted the importance of assessing an industry's performance in the context of variation across countries. While this may serve as an important step to learn about the dynamics of a particular (set of) industry(ies), it says very little about the characteristics of the manufacturing sector of a particular country as a whole. Consequently, and in order to assess the degree to which a country's manufacturing sector is comprised of industries with a certain set of characteristics (like the ones described by the characterization of runner industries), a simple ratio of the value added and employment share of runner industries in total manufacturing value added and employment is proposed. This concept is referred to as 'runner exposure': to this end, we use the term global runner exposure when evaluating the share of industries that have been identified as runners at the global stage. **We use the same term to refer to income group runners (income group runner exposure) and country-level runners (country-level runner exposure) when shares are calculated on the basis of runners identified at the income group level and country level, respectively.**

We can thereby obtain two simple indicators that allow us to assess the share of manufacturing industries in an economy that have experienced inclusive and sustained growth in the past. If the share of runner industries in a given country's total manufacturing is very low, for example, it may indicate a higher risk of jobless growth in the wake of technological adoptions, which would deserve the attention of policymakers, especially in terms of employment protection measures. As illustrated in Appendix C, higher and prolonged exposure to industries classified as global runner industries are associated with economically more advanced countries.

In Table 5.5 runner industry exposure is calculated on the basis of country-level runner industries for Viet Nam and Morocco and compared with the share of runners in total value added identified at the lower middle-income country level.[28] Major differences between the country-level runner exposure analysis and its lower middle-income counterpart in Table 5.5 are evident: for example, the runner value added share increases from 27 per cent to 88 per cent and an even higher increase (from 15 per cent to 91 per cent) is observed for the runner employment share for Viet Nam. On the other hand, the difference between Morocco's income group runner exposure and the country-level runner exposure is notably smaller. This is interesting for two reasons. On the one hand, Morocco's medium high-technology industries have more weight on the country's runner industry profile compared to Viet Nam, as the chemical, machinery and precision instruments industries are part of Morocco's runner industries but not Viet Nam's. On the other hand, and despite the fact that Morocco has eight runner industries (compared to seven for Viet Nam), its runner industries' value added and employment shares are 33 per cent to 43 per cent lower, respectively, than Viet Nam's. This means that the share of industries with favourable productivity and employment trajectories constitute a much smaller share of the Moroccan manufacturing sector in comparison to Viet Nam. The table also adds the average share of lower middle-income runners post-2000 in total manufacturing value added, which reinforces the idea that Viet Nam and Morocco perform above average in terms of value added runner exposure (as well as employment for the case of Morocco).

Table 5.5: Viet Nam's runner industry exposure in 2015, post-2000 runners, sorted by runner value added and employment share in descending order

	Income group runner exposure		Country-level runner exposure	
Country	Value added share	Employment share	Value added share	Employment share
Morocco	0.33	0.25	0.55	0.48
Viet Nam	0.27	0.15	0.88	0.91
Lower middle-income average	0.25	0.20	NA	NA

Note:

INDSTAT 2 rev.3, 2000-2017. Runner exposure shares based on lower middle-income countries and shown for 2015

Despite some limitations in the coverage of real value added data, the important take away from Table 5.5 is that country-specific shares of runners for both Viet Nam and Morocco are much higher than the share of runners calculated using those identified at the lower middle-income country level. This means that Viet Nam and Morocco are much more exposed to runner industries than what is expected on average and look more resilient to jobless growth. Morocco is not as resilient as some low-technology industries (e.g. food and beverages and wearing apparel) are traditionally preponderant at lower income levels and are not identified as country-level runners.

RUNNERS SECTION SUMMARY

To conclude, this section has applied the concept of runner industries to identify growth dynamics. The example of the Vietnamese and Moroccan manufacturing sector is used to relate country-level dynamics to more general patterns observed amongst the set of lower middle-income countries. Our analysis highlights the fact that the concept of runner industries is relative and therefore sensitive to the choice of data sample. While the concept of runner industries is certainly a challenging instrument to apply, it has a huge advantage over more static classifications: following the notion that there is no 'one-size-fits-all' approach to manufacturing policy in general and technology adoption in particular, the runner industries framework allows for a flexible identification of growth-enhancing industries. The instruments presented in this tool can be tailored and streamlined to meet policymakers' specific assessment needs. At the same time, the runner instrument has also highlighted that even within a narrowly defined window of analysis, differences in the respective growth rates are reflective of country-specific effects and should therefore be given close consideration when interpreting the runner industry assessment. For a careful consideration of the runner industry classification of a particular country/set of countries, it is important to contextualize the differences identified relative to a suitable reference group (e.g. income groups) as well as the global trend (global runners). Viet Nam, by and large, reports a disproportionately high contribution of employment-led industries (where positive employment growth outpaces value added growth, thereby leading to a negative productivity growth rate). Only about half of Moroccan manufacturing value added and employment has been created by industries with a positive growth trajectory of value added and employment. Policymakers from both countries should be aware of these dynamics as they may have important ramifications, particularly in the context of adoption of new technologies.

Appendix

A Leading Industry 4.0 exporter

Based on UNIDO (2020), industrial robots (IR), computer-aided design and manufacturing (CAD-CAM) and additive manufacturing (AD) are core Industry 4.0 technologies for which there is available data on trade (see Appendix F for a detailed classification).

The exports market capital of Industry 4.0 goods was valued at US$ 77 billion in 2017 alone. World exports are characterized on the basis of concentrated distribution. Figure A.1 presents the export share of Industry 4.0 goods of each major exporter in the market. The top seven exporters make up more than half of all world exports of Industry 4.0 goods.

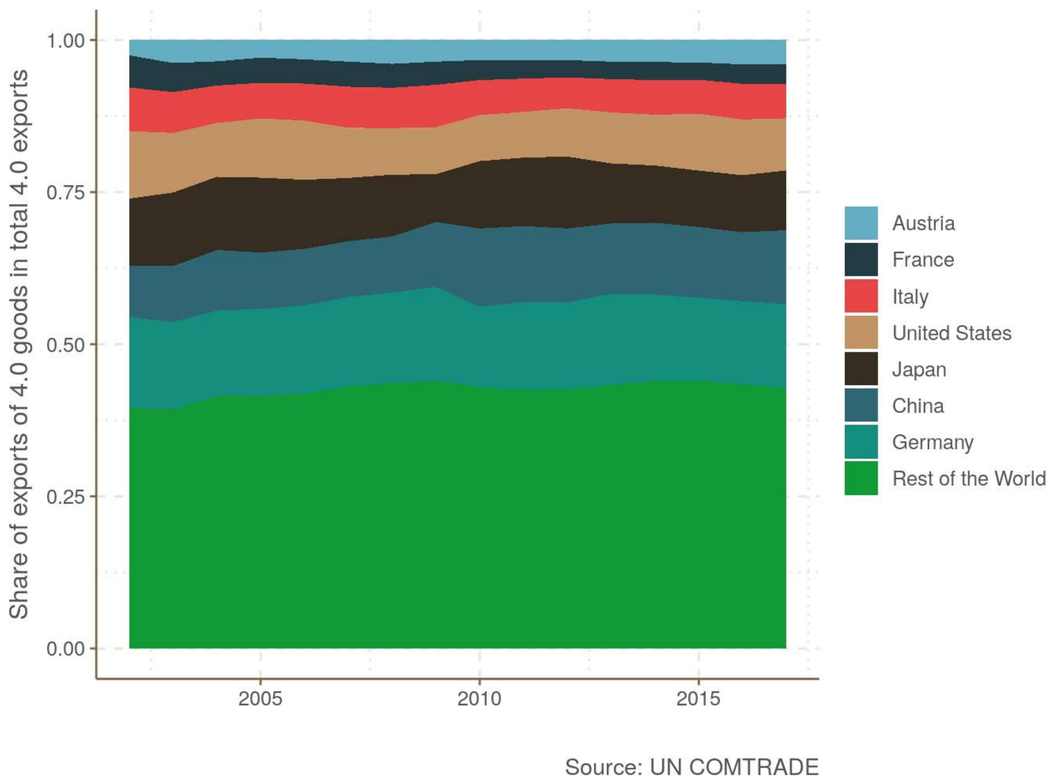


Figure A.1: Exports of Industry 4.0 goods

B Runner industry analysis in detail

When conducting the runner analysis for different time spans, a different set of industries will frequently qualify as runners. Please note that the statement 'The results of the runner analysis depend on the time dimension' is **not a true statement**. The results of such analyses do not necessarily depend on the time span but on **how the variables of interest have changed over that period.**

To better explain this, consider Figure B.1: the black line depicts the stylized movement of productivity (y-axis) over time (x-axis). We also see that this line is hump-shaped. Because of this property, we will find different results when evaluating this industry depending on the time span we use for the runner industry analysis:

- Moderate positive growth for the period associated with the orange line;
- High positive growth for the period associated with the blue line;
- Negative growth for the period associated with the green line.

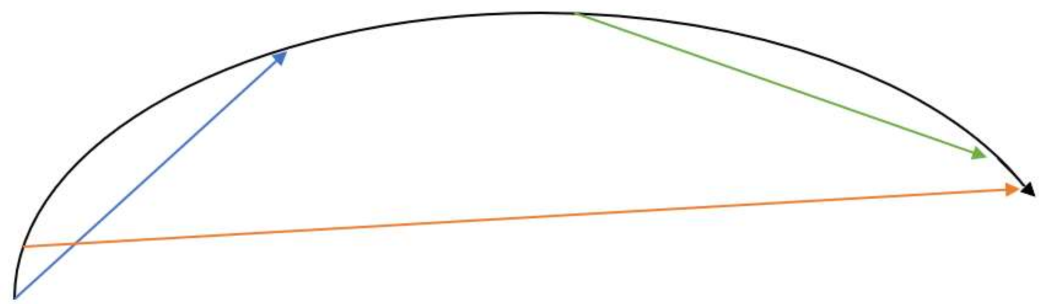


Figure B.1: Stylized productivity trajectory

If productivity had followed a straight line (the slope is irrelevant for this), we would have found the **same dynamics for this industry, irrespective of the time frame considered**.

C Rationale of runner exposure analysis

The identification of runner industries offers a new way to highlight favourable industry-related performance patterns. Given the characteristics of a runner industry, i.e. a positive productivity, value added and employment growth rate, a high share of runner industries in a country's total manufacturing implies that a country's manufacturing sector, on average, displays favourable productivity growth dynamics while also sustaining employment growth; both of which are highly desirable outcomes.

The idea of having a high share of runner industries in total manufacturing imposes an interesting enigma: the higher the share of industries that have grown over time, the higher the country's economic output. Yet this does not conflict with the goal of achieving a high share of medium high-technology industries to form the backbone of a sustainably developing manufacturing sector. This is due to the following two reasons:

- Firstly, the overlap between the concept of medium high-technology industries and that of runners is substantial: the majority of identified runner industries belong to the group of medium high-technology industries (see Table 5.3). For the post-2000 sample, this increases to six out of seven industries. In this sense, the overlap created through the empirical identification of runner industries can be understood as a confirmation of the positive effect of technological advancements in manufacturing that can also be employment enhancing.

- Secondly, the concept of runner industries adds an additional layer of dynamism to the process as it enables us to capture within-industry structural change dynamics. Because of its dynamic nature, the concept of runner industries offers a gateway to an organic identification of newly emerging trends in manufacturing development: it allows for the possibility to capture an industry's productivity and employment dynamics which may in fact transition from a low to a medium high-technology configuration as a consequence of adoption of new technology. This transition may then be accompanied by an increase in both productivity as well as employment, requiring a specific and novel set of skills. While such dynamics can be unveiled using the concept of runner industries, they would remain hidden if the fixed classification of technology groups is applied. Nonetheless, it goes without saying that the concept of runner industries should not be seen as a competing but rather as a complementing measure for identifying favourable manufacturing industry compositions and should not replace the existing technology-centred paradigm.

If, for example, the share of runner industries in a country's total manufacturing is very low, it may indicate a higher risk of jobless growth in the wake of technological adoptions, which deserves the attention from policymakers, especially in terms of employment protection measures.

We have shown in previous sections that higher and prolonged exposure to industries that are not necessarily the best performers in terms of job creation, may in the long term be associated with lower income levels. The evidence is produced by calculating average share of *global runners* across developed and developing countries. The *global runner*s exposure may be useful to produce country rankings based on the share of runners in either total manufacturing value added or employment. We illustrate this in Table C.1, which ranks the countries based on their exposure to post-2000 runner industries for the year 2016, by the share of global runners' value added and employment in descending order. What becomes apparent is that out of the top-10 countries, eight belong to the group of high-income countries while Viet Nam ranks 42nd out of 57 in terms of the share of its runners' value added. In other words, 54 per cent of value added contribution (33 per cent of employment contribution) to total manufacturing value added (employment) in 2016 came from industries that reported positive value added and employment growth rates in the post-2000 period. This places Viet Nam in the 18th percentile of ranked countries in terms of value added generation (2nd percentile for employment).[29]

Table C.1 is only a snapshot in time and indicates that there seems to be somewhat of a separating pull between high-income and lower middle-income countries (as well as lower income countries which are not shown in this table) in terms of their *global runners* exposure. The relationship between a high share of *global runner*s industries and economic performance can also be summarized visually: in Figure C.1, the shaded areas denote the share of runner industries in manufacturing value added for different percentiles of the data. In the darkest shade of grey, the minimum to 20th percentile of value added runner share contributions is illustrated over time, followed by the 20th to 40th percentile in a lighter shade of grey, etc. The upper edge of the lightest grey represents the country that reported the highest share of runners in value added between the years 1990 to 2017. The coloured lines identify the average global runner share for the set of developed, i.e. high-income and developing (all but high-income) countries. In other words, for the average developed economy (which is obtained by calculating the average runner industry exposure across all high-income countries), the value added share of *global runners* industries in manufacturing increased from around 40 per cent in 1999 to around 50 per cent in 2016. Contrary to this, the corresponding share for the group of developing countries remained stable at around 40 per cent.

Table C.1: Ranking of exposure to runner industry in 2016, post-2000 runners, sorted by the share of runners' value added and employment in descending order

Rank (of 57)	Country	Runner value added share	Runner employment share	Income group
1	Switzerland	0.89	0.82	High-income
2	Luxembourg	0.87	0.90	High-income
4	Germany	0.80	0.79	High-income
6	France	0.79	0.79	High-income
7	Philippines	0.78	0.66	Lower middle-income
8	Hungary	0.77	0.74	High-income
9	Netherlands	0.76	0.77	High-income
12	Colombia	0.74	0.63	Upper middle-income
13	Croatia	0.74	0.65	High-income
20	Egypt	0.69	0.53	Lower middle-income
21	Indonesia	0.69	0.48	Lower middle-income
32	Ukraine	0.64	0.62	Lower middle-income
35	Bulgaria	0.62	0.57	Upper middle-income
40	Republic of Moldova	0.58	0.57	Lower middle-income
42	Viet Nam	0.54	0.33	Lower middle-income
44	Mongolia	0.51	0.42	Lower middle-income
46	Sri Lanka	0.50	0.36	Lower middle-income
47	India	0.47	0.50	Lower middle-income
57	Kyrgyzstan	0.17	0.50	Lower middle-income

Note:
INDSTAT 2 rev.3, 2000-2017, runner exposure shares shown for 2016. Ranking based on a total of 57 countries

Similarly, considering the two most recent decades characterized by a fast-paced adoption of new technologies, the set of runner industries identified for the post-2000 period in Figure C.2 exhibit the same characteristics as that of the previously highlighted full sample: the average share of runners in developed economies remains approximately 10 per cent higher than that of developing countries. This is particularly insightful as the set of runner industries identified for the post-2000 sample was complemented by an additional high-technology (chemical) and low-technology (food and beverages) industry.

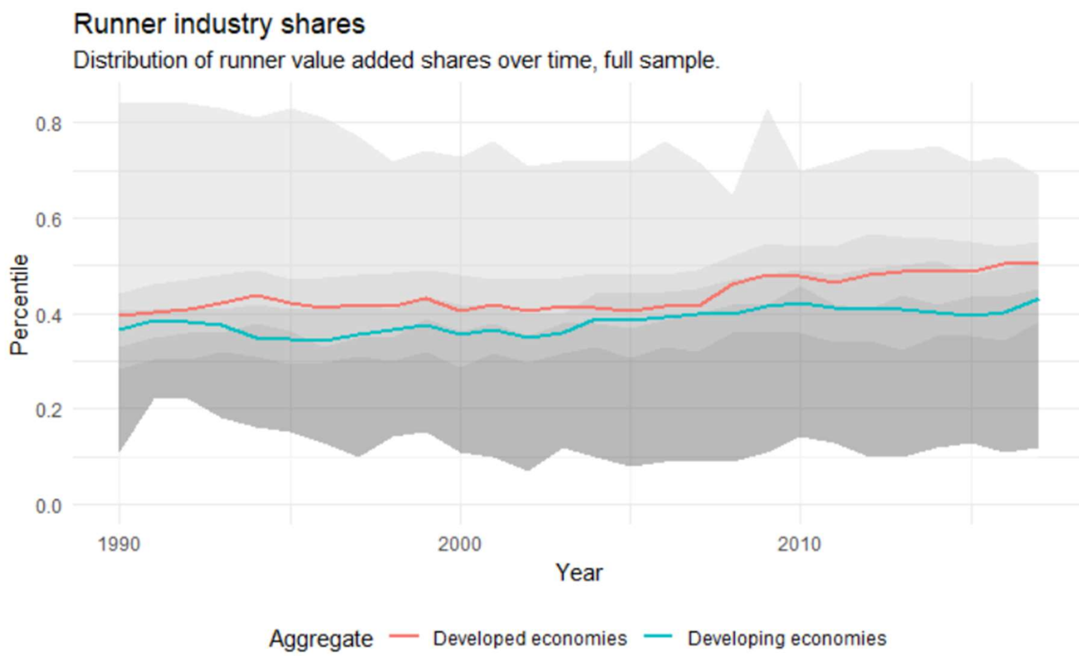


Figure C.1: Visualization of concept

As such, Figure C.1 and Figure C.2 are generalizations of the country- and income group-specific dynamics discussed in Table C.1.

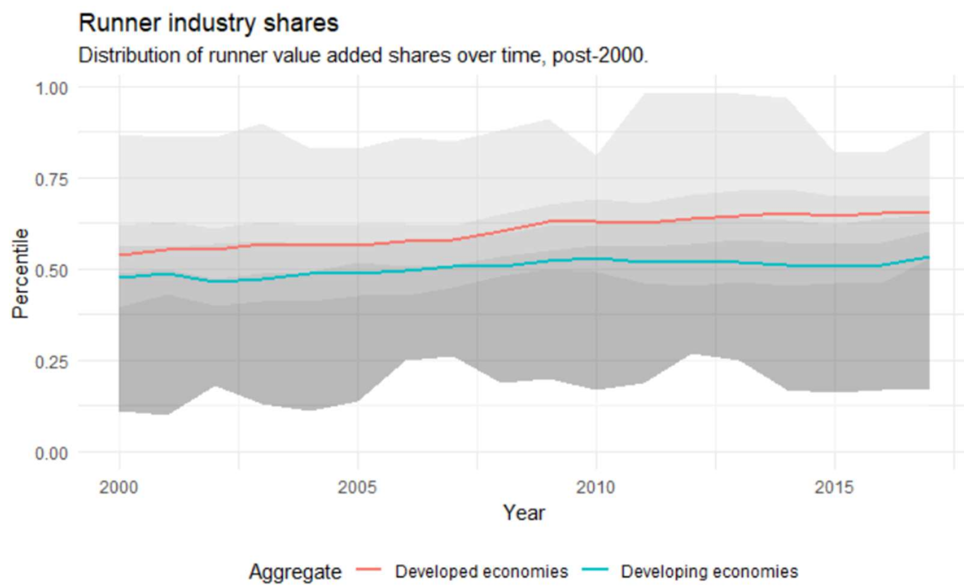


Figure C.2: Visualization of concept

As the shares of runners in developing countries may be underestimated because IIPs may decrease for certain industries in some countries, we use available value added data particularly for this group of countries and conduct a robustness exercise to create the same graphs by using nominal values. Applying the same analysis using nominal data (at the cost of not correcting for inflation), results prove to be qualitatively similar and reinforce the robustness of the empirical regularity.

Further evidence of the robustness of the result is provided in Figure C.3, which illustrates how the sample's data coverage has improved over the years. This figure is insightful and may alleviate concerns that the set of identified runner industries is severely under-reported in the developing compared to developed economies of our sample. If that were the case, it could be argued that the difference between the shares of runner exposure of developing and developed countries may simply be due to the fact that these industries are simply not reported for developing countries. However, as Figure C.3 illustrates, this does not seem to be the case as the data coverage between developing and developed countries does not appear to differ systematically. This becomes apparent when comparing the differences in missing real value added, productivity, as well as the employment-to-population ratio in Figure C.3.

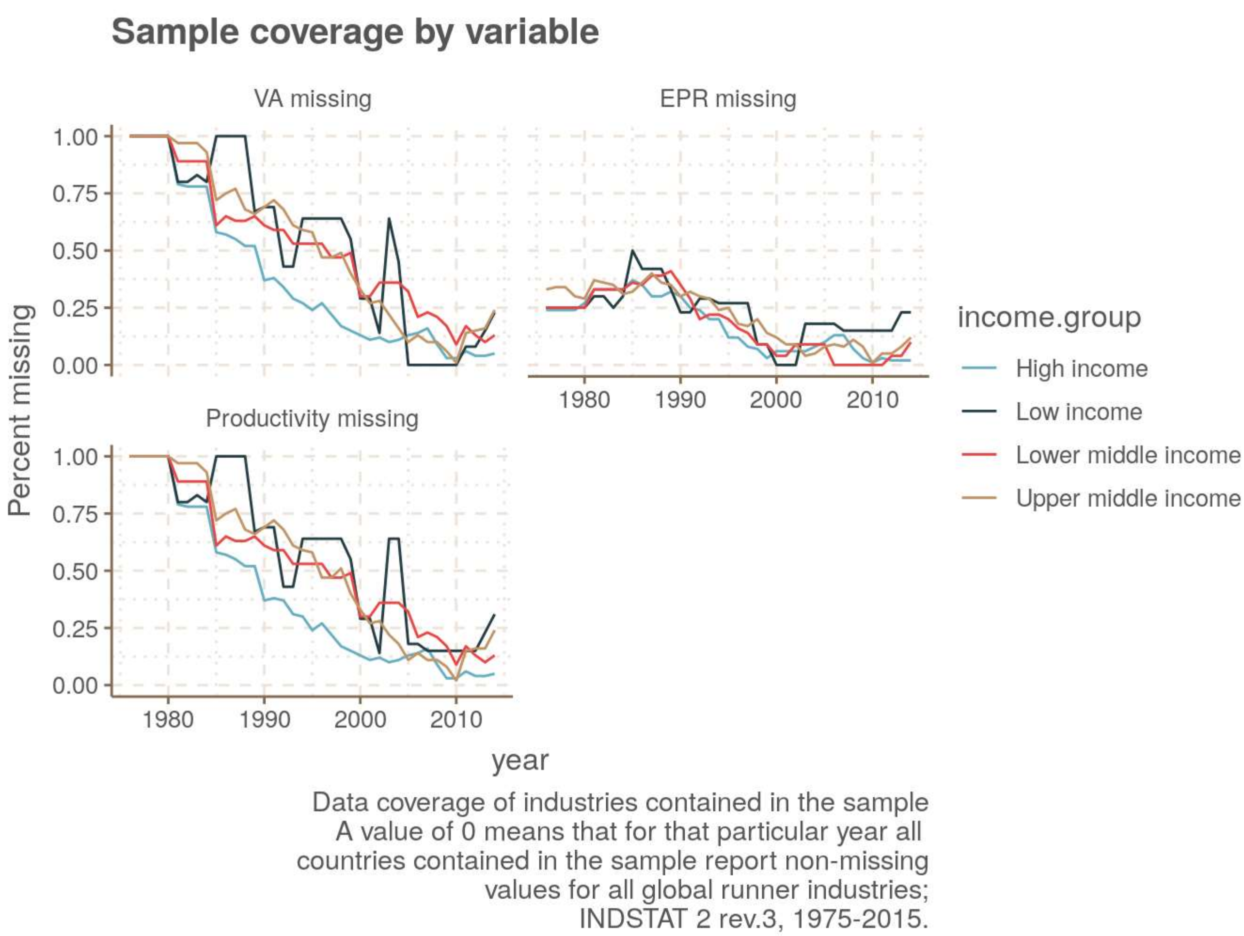


Figure C.3: Sample coverage of runner industries across income groups

On the basis of the runner industry framework, the set of runner industries obtained for the different income group aggregates can be obtained as summarized in Table C.2.

Table C.2: Summary of runner industries classification by aggregate

Manufacturing Industries	High-income runner, full sample	High-income runner, post-2000	Upper middle-income group runners, full sample	Upper middle-income group runners, post-2000	Lower income group runners, full sample	Lower income group runners, post-2000	Global runners, full sample	Global runners, post-2000
15: Food and beverages			Yes	Yes		Yes	Yes	Yes
16: Tobacco								
17: Textiles								
18A: Wearing apparel								
20: Wood products			Yes	Yes				
21: Paper			Yes	Yes				
22: Printing and publishing			Yes					
23: Coke and refined petroleum								
24: Chemicals			Yes	Yes	Yes	Yes		Yes
25: Rubber and plastic	Yes		Yes	Yes			Yes	Yes
26: Minerals				Yes				
27: Basic metals								
28: Fabricated metals	Yes		Yes	Yes	Yes	Yes	Yes	Yes
29C: Machinery			Yes	Yes				
31A: Electrical machinery					Yes	Yes	Yes	Yes
33: Precision instruments	Yes		Yes	Yes				Yes
34A: Motor vehicles			Yes	Yes	Yes	Yes	Yes	Yes
36: Furniture, n.e.c					Yes	Yes		

Note: INDSTAT 2 rev.3.

To this end, Table C.3 summarizes the number of countries that reported positive productivity, value added as well as employment growth rates.

Table C.3: Full sample runners: counted positive growth rates (countries) per industry

	Full country sample			
Identified runner industries	Productivity	Real value added	Employment-population ratio	Total number of countries
15	42	48	34	69
25	45	51	43	71
28	47	48	37	74
31A	8	9	9	14
34A	38	38	34	55

Note: INDSTAT 2 rev.3, 1963-2017

Detailed explanation of runner industry calculation for *global or income group runners*

1. Calculate CAGRs for value added, employment and productivity for the selected time window for all selected countries separately. The result will be three growth rates (of value added, employment, productivity) for each country and industry considered.
2. Calculate averages according to the desired form of aggregation: for example, if the focus are global runners of a particular industry, the average growth rate of value added, employment and productivity across all countries of the sample must be calculated. Conversely, if the focus are income group runners exclusively, the averages would only be calculated for the set of countries that belong to the same income group.
3. The result of Step 2 are three growth rates (of value added, employment and productivity) that correspond to that of the average of the aggregate considered. These three aggregated growth rates are then evaluated against the previously introduced scheme: only if all three of these growth rates are positive, does the respective aggregate qualify as a runner industry.

D Employment data from the United Nations INDSTAT vs. ILO

When total manufacturing employment data is used in this tool, it is sourced from the ILO database (ILO 2019). Alternatively, for countries' total manufacturing employment and total employment, the user can alternatively aggregate INDSTAT time series that are used whenever industry-specific numbers are presented here.

This would affect indicators 3.9 and 3.12 as well as graphs 4.3, 4.5 and 4.6. Using INDSTAT instead of ILO results in the following figures:

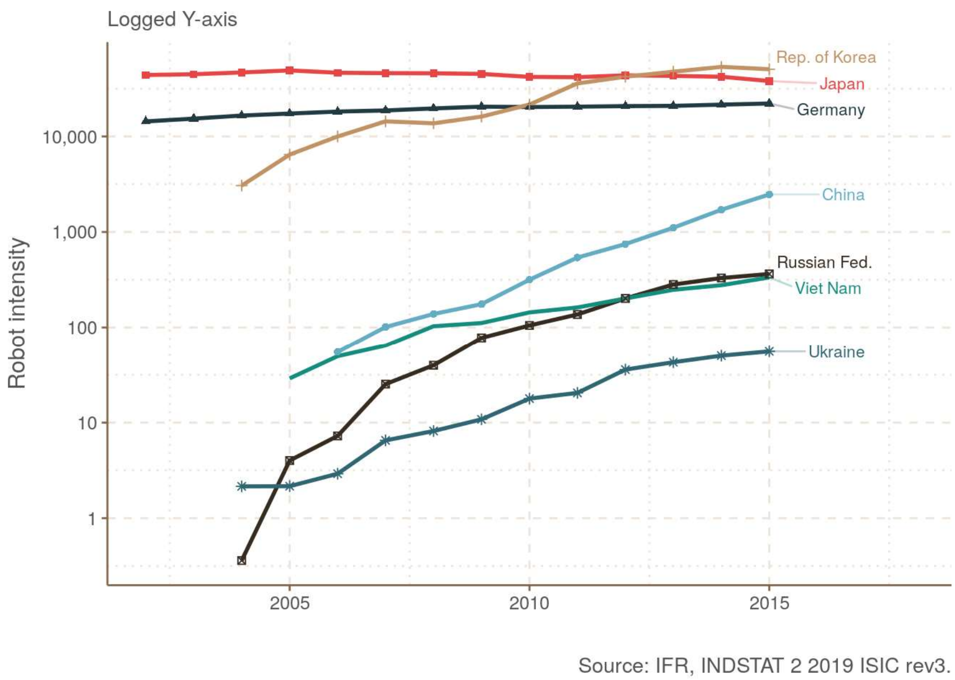


Figure D.1: Robot intensity: robots per 1 m. manufacturing employees

Figure D.2: Vulnerability to robotic automation

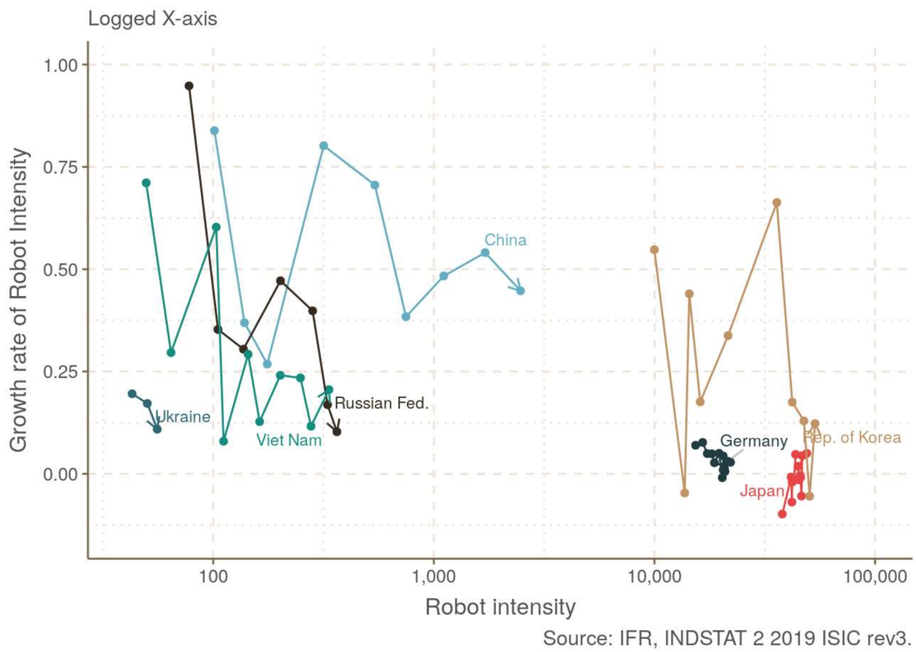


Figure D.3: Maturity effect of automation

Using INDSTAT employment data for total (manufacturing) employment instead of ILO data does not change the overall results qualitatively.

E Deflation of nominal value added series

Deflation, i.e. eliminating the effect of inflation, of the value added series is a necessary intermediate step as high growth rates of nominal value added might be the consequence of strong price increases (inflation). Hence, nominal value added growth rates might wrongly indicate an increase in productivity, even though the effect is actually only driven by the variation in prices over time. Consequently, these price effects must be eliminated from the nominal value added series. This is done by deflating the nominal value added sequences in order to obtain their real value added representation.

For the purpose of this analysis, we construct real value added sequences based on the methodology proposed in Haraguchi and Amann (2019), which is calculated as:

$$rVA_{ijt} = nVA_{ijt} \times Deflator_{ijt}$$

$$Deflator_{ijt} = \frac{nGO_{bjt}}{nGO_{ijt}} IIP_{ijt}$$

where nVA, rVA denotes nominal and real value added in period ***t***, industry ***j*** and country ***i***, respectively. The $Deflator$ is given by the ratio of nominal gross output nGO in the base year ***b*** (which is set to ***b*** = 2010) relative to nominal gross output in period ***t*** and its corresponding Industrial Index of Production IIP. The benefit of calculating real value added in this form is that it allows for the creation of an industry-specific deflator across countries, thereby facilitating the construction of comparative measures, which is particularly important for a cross-country comparator analysis.

Technical discussion on missing data.

As discussed in the main body of this document, the real value added series appear to be missing in its final form in some cases as described by the equations above. This section briefly illustrates one possible scenario how this may occur.[30]

As such, Figure E.1 reveals that for none of the years, Viet Nam's medical, precision and optical instruments industry has all necessary data series for us to recover real value added on the basis of the methodology proposed in this document at the time of writing.

H14 fx Σ = =E14*(F14/F14*G14)

	A	B	C	D	E	F	G	H
1	Country Description	Year	ISIC	ISIC Description	Output	Value added	Index numbers of Industrial production	Real Value Added
2	Viet Nam	1998	33	Medical, precision and optical instruments	32430208	9380389		
3	Viet Nam	1999	33	Medical, precision and optical instruments	34697409	9921778		
4	Viet Nam	2000	33	Medical, precision and optical instruments	79441337	22696617		
5	Viet Nam	2001	33	Medical, precision and optical instruments	84026214	26495653		
6	Viet Nam	2002	33	Medical, precision and optical instruments	87974083	29381769		
7	Viet Nam	2003	33	Medical, precision and optical instruments	117662735	35483947		
8	Viet Nam	2004	33	Medical, precision and optical instruments	162168170	30125242		
9	Viet Nam	2005	33	Medical, precision and optical instruments		36075347		
10	Viet Nam	2006	33	Medical, precision and optical instruments		42984234		
11	Viet Nam	2007	33	Medical, precision and optical instruments		101990645		
12	Viet Nam	2008	33	Medical, precision and optical instruments		171674406		
13	Viet Nam	2009	33	Medical, precision and optical instruments		175258084		
14	Viet Nam	2010	33	Medical, precision and optical instruments		221573472	1	0
15	Viet Nam	2011	33	Medical, precision and optical instruments			2	#DIV/0!
16	Viet Nam	2012	33	Medical, precision and optical instruments			2.39	#DIV/0!
17	Viet Nam	2013	33	Medical, precision and optical instruments			2.87	#DIV/0!
18	Viet Nam	2014	33	Medical, precision and optical instruments			7.99	#DIV/0!
19	Viet Nam	2015	33	Medical, precision and optical instruments			9.89	#DIV/0!
20								

Figure E.1: Visualization of concept

F Industry 4.0 goods in trade statistics

Table F.1: Industry 4.0 goods (HS 2002 classification)

Industry 4.0 goods cluster	HS 2002 capital goods classification
Additive Manufacturing	847710 (“Injection-moulding machines”);
	847720 (“Extruders”);
	847730 (“Blow moulding machines”);
	847740 (“Vacuum moulding machines and other thermoforming machines”);
	847751 (“Other machinery for moulding or otherwise forming: For moulding or rethreading pneumatic tires or for moulding or otherwise forming inner tubes”);
	847759 (“Other machinery for moulding or otherwise forming”); and
	847790 (“Parts”).
CAD-CAM	845811 (“Horizontal lathes: Numerically controlled”);
	845819 (“Other lathes: Numerically controlled”);
	845921 (“Other drilling machines: Numerically controlled”);
	845931 (“Other boring-milling machines: Numerically controlled”);
	845951 (“Milling machines, knee-type: Numerically controlled”);
	845961 (“Other milling machines: Numerically controlled”);
	846011 (“Flat-surface grinding machines, in which the positioning in any one axis can be set up to an accuracy of at least 0.01 mm: Numerically controlled”);
	846021 (“Other grinding machines, in which the positioning in any one axis can be set up to an accuracy of at least 0.01 mm: Numerically controlled”);
	846031 (“Sharpening (tool or cutter grinding) machines: Numerically controlled”);
	846221 (“Bending, folding, straightening or flattening machines (including presses): Numerically controlled”);
	846231 (“Shearing machines (including presses), other than combined punching and shearing machines: Numerically controlled”);
	846241 (“Punching or notching machines (including presses), including combined punching and shearing machines: Numerically controlled”).
Robotics	847950 (“Industrial robots, not elsewhere specified or included”)

Note: Source: based on UNIDO (2020)

An important word of caution regarding this part of the approach relates to the fact that the imperfect overlap between these technologies and the HS codes inevitably means that earlier vintages of technology (i.e. 3IR technologies) are also included in the classification. Despite this, the data should provide useful insights into the production and use of advanced technologies in these domains and are a means for identifying countries with the capability to use (and potentially benefit) from such technologies.

G Intra-industry structural change

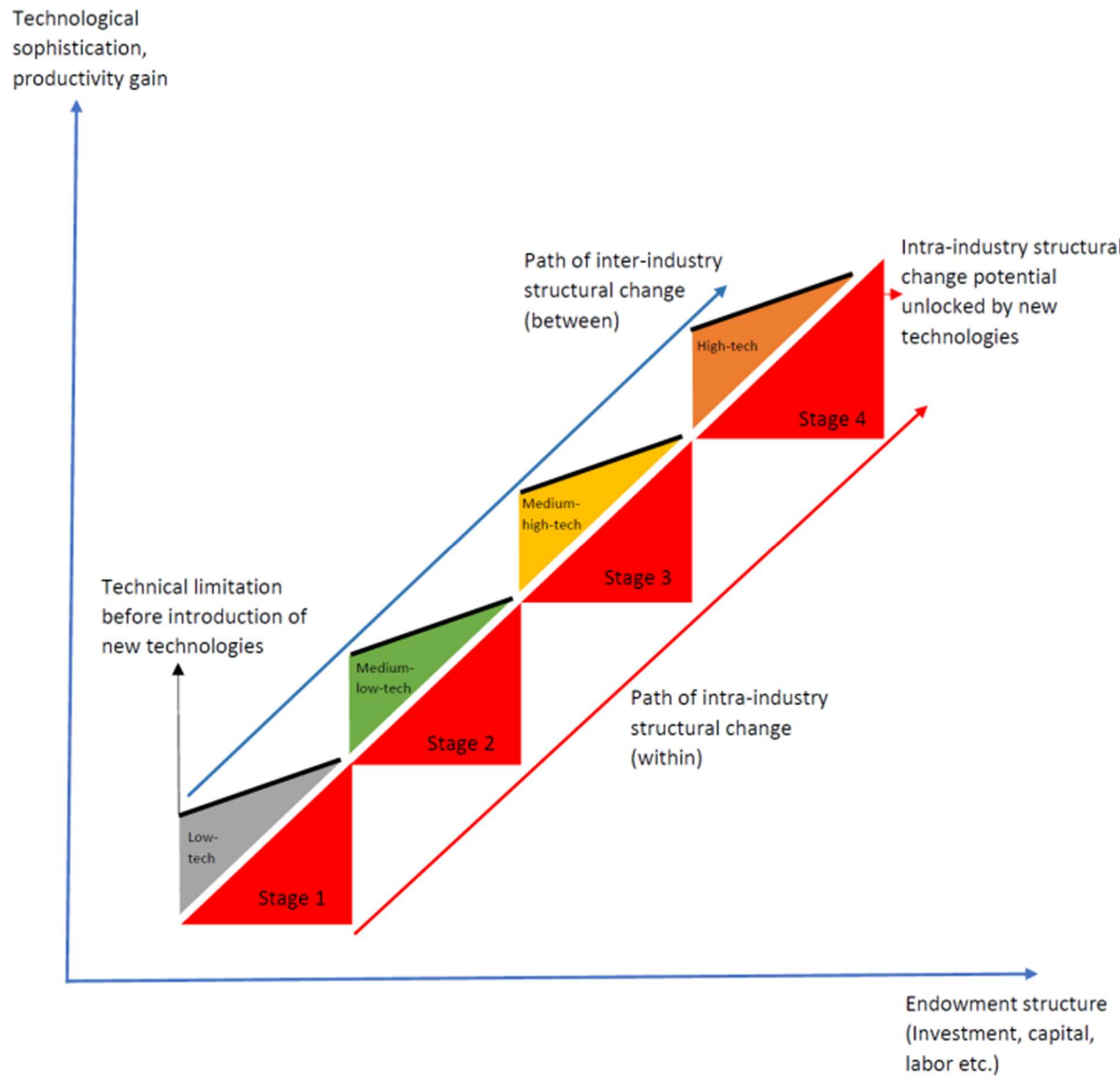


Figure G.1: Intra-industry structural change

The concept of intra-industry upgrading is illustrated in G.1:

- Schematic diagram:
  - Red path: intra-industry / within-industry structural change (i.e. an industry, from stage 1 to 4, depending on technological sophistication)
  - Blue path: inter-industry / between-industry structural change (shifting resources from low-technology to medium-high-technology industries)
- Departure: for instance, in the early stages of the development of the food and beverages industry, the country's window of opportunity could be low-technology labour-intensive food production activities (grey box: low-technology).
- Capability enabling with a long-term commitment from the government and other stakeholders, i.e. increasing investment, etc., the country starts accumulating factor

resources to upgrade its endowment structure (moving along the horizontal axis, from left to right).

- Reaching technical limitations (cap of the grey box: low-technology): accumulation of factor resources (investment, capital, etc.) which entails full exploitation of labour cost advantages (also economies of scale, etc.). In a static environment, the technical limitation in the food and beverages industry is reached.
- Decision-making: depending on the technological innovation capability of Viet Nam, breakthrough and a mass diffusion of new technologies (i.e. 4IR technologies) could unlock the potential for Viet Nam to further deepen its food and beverages industry (a possibility of intra-industry leapfrogging, red box from stage 1 to 2/3). This within-industry structural change / intra-industry upgrading may provide equal if not more productivity gain for Viet Nam compared to its medium-high-technology path between-industry structural change, i.e. shifting resources from the food and beverages industry to the non-metallic mineral industry (i.e. from low-technology to medium low-technology industry).

H UN COMTRADE classification by Broad Economic Categories (Rev.4)

Compared to other classifications, such as HS 2002, that can differentiate very specific goods, 'BEC' summarizes goods in broad economic categories. At the time of publication, (September 2019), UN COMTRADE (2019) was using revision 4 of the BEC classification. The broad categories include:

1. Food and beverages
2. Industrial supplies not elsewhere specified
3. Fuels and lubricants
4. Capital goods (except transport equipment) and parts and accessories thereof
5. Transport equipment and parts and accessories thereof
6. Consumer goods not elsewhere specified
7. Goods not elsewhere specified.

The System of National Accounts (SNA) defines the broadest types of goods as capital goods, intermediate goods and consumption goods. Based on that, the UN COMTRADE BEC classification identifies the following (sub)groups as capital goods:

- 41 Capital goods (except transport equipment)
- 521 Other industrial transport equipment

The sum of these two groups represent the 'capital goods' in this module.

I Progression patterns in import and export dynamics

Some clear empirical evidence in favour of a technological progression can be derived, which is reflected in changes of the import/export structure of capital and Industry 4.0 goods as economies grow richer. In this section, we will take a closer look at the underlying components.

We introduced the following classification:

RCA import	RCA export	Group
< 1	> 1	specialized producer
> 1	> 1	specialized producer and user
> 1	< 1	specialized user
< 1	< 1	non-specialized

We identify a strong regularity when we compare the classification patterns of capital goods vs. Industry 4.0 goods: in 90 per cent of the recorded cases in our data, countries are in a 'higher' (more specialized) or in the same group for capital goods as for Industry 4.0 goods. In other words, they are 'leading in capital goods but trailing in Industry 4.0 goods' in the sense that they have a higher proclivity to export capital goods **before they export Industry 4.0 goods.** Table I.1 provides a more detailed account of that observation.[31] In 82 per cent of the cases, a non-specialized country in capital goods is also found to be non-specialized in Industry 4.0 goods. On the other hand, at least one-third of specialized producers in capital goods are also specialized producers in Industry 4.0 goods.

Table I.1: Progression matrix, all countries

	Industry 4.0 goods			
Capital goods	Non-specialized	Specialized user	Specialized producer and user	Specialized producer
Non-specialized	0.81	0.14	0.03	0.01
Specialized user	0.63	0.34	0.02	0.01
Specialized producer and user	0.45	0.28	0.19	0.09
Specialized producer	0.25	0.21	0.22	0.32

Note: Percentages; rows sum up to 1.

This general regularity also applies when conducting the same analysis based on income group as shown in the tables below.

Table I.2: Progression matrix, high income

	Industry 4.0 goods			
Capital goods	Non-specialized	Specialized user	Specialized producer and user	Specialized producer
Non-specialized	0.76	0.11	0.09	0.03
Specialized user	0.74	0.19	0.05	0.02
Specialized producer and user	0.53	0.10	0.25	0.12
Specialized producer	0.19	0.05	0.31	0.44

Note: Percentages; rows sum up to 1.

Table I.3: Progression matrix, upper middle income

	Industry 4.0 goods			
Capital goods	Non-specialized	Specialized user	Specialized producer and user	Specialized producer
Non-specialized	0.80	0.19	0	0
Specialized user	0.41	0.58	0.01	0
Specialized producer and user	0.07	0.93	0	0
Specialized producer	0.19	0.81	0	0

Note: Percentages; rows sum up to 1.

Table I.4: Progression matrix, lower middle income

	Industry 4.0 goods			
Capital goods	Non-specialized	Specialized user	Specialized producer and user	Specialized producer
Non-specialized	0.84	0.16	0	0
Specialized user	0.70	0.30	0.01	0
Specialized producer and user	0.70	0.30	0	0
Specialized producer	0.69	0.31	0	0

Note: Percentages; rows sum up to 1.

Table I.5: Progression matrix, low income

Capital goods	Industry 4.0 goods			
	Non-specialized	Specialized user	Specialized producer and user	Specialized producer
Non-specialized	0.93	0.07	0	0
Specialized user	0.79	0.21	0	0

Note: Percentages; rows sum up to 1.

Figures 4.4 and 4.8 displayed average RCAs by income group. Averages were calculated for all years and per income group. A more detailed illustration of these patterns follows:

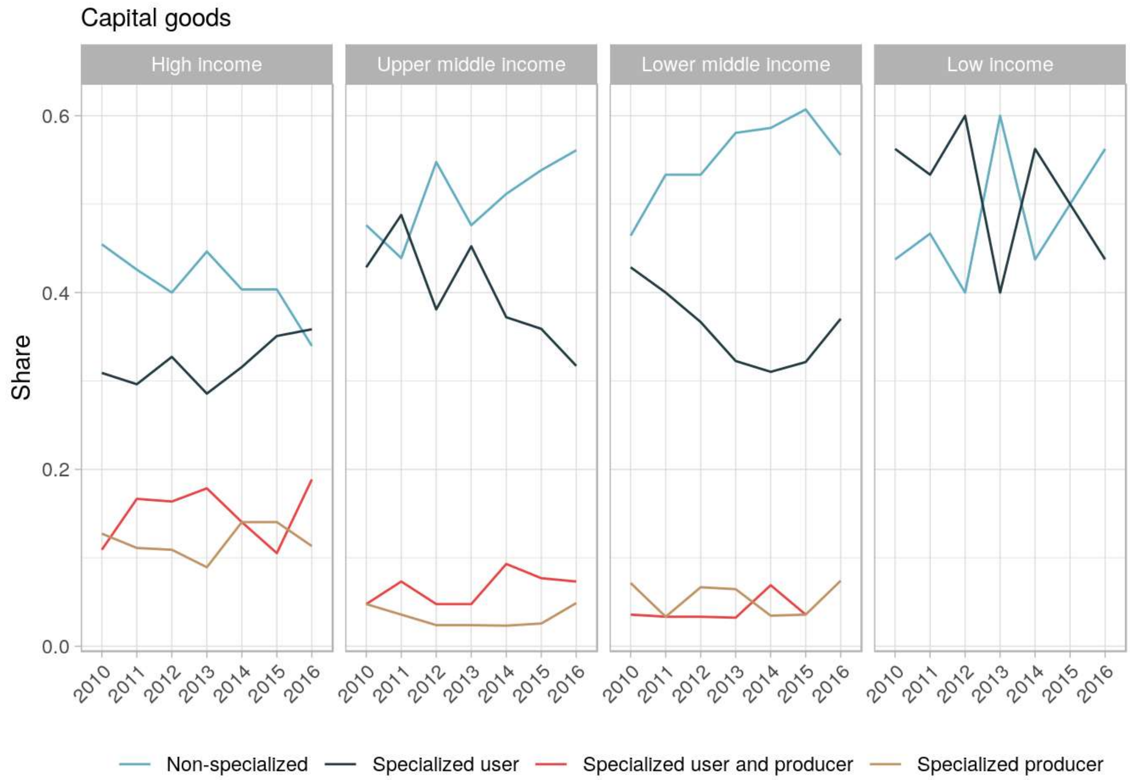


Figure I.1: Classification of countries by year and income group

This depiction shows the shares of users and producers by income group across time. Based on this illustration, the following conclusions can be made:

- On average, low-income countries are non-specialized in capital goods, with neither above average imports or exports. Around 40 per cent of them are specialized users, meaning they import and use some capital goods, and are starting the adoption process.
- On average, lower middle-income countries have higher shares of specialized users than low-income countries and between 5 per cent and 10 per cent of them also export capital goods above the world average.

- On average, higher middle-income countries have a higher share of specialized users and producers compared to lower middle-income countries and they already have some specialized producers.
- On average, high-income countries have the highest share of specialized producers and the lowest share of specialized users.

The same can be done for 4.0 goods, resulting in the following figure:

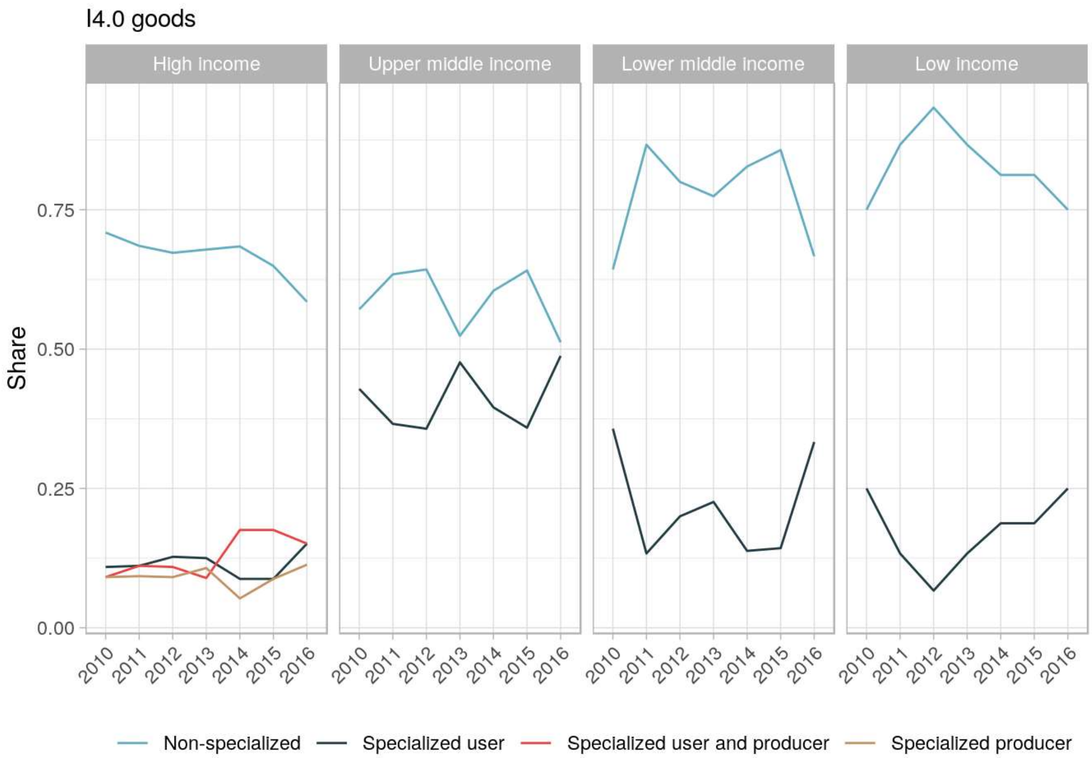


Figure I.2: Classification of countries by year and income group

Only high-income countries are above average exporters of goods based on the newest wave of production technology. Additionally, the higher the income, the higher the share of countries that are specialized users, i.e. above average importers of modern production technologies.

When we compare countries across groups of goods (capital goods vs. 4.0 goods), we find a very consistent pattern: the majority of countries (about 90 per cent) are specialized producers and users of capital goods before they use and produce Industry 4.0 goods. There are only a handful of exceptions where a country would be classified as a specialized producer of the newest technology but not of capital goods. This should convince policymakers that a solid manufacturing basis that uses different vintages of technologies is a prerequisite for becoming a specialized producer of the most modern technologies. This statement holds for virtually all low-income countries as well as the lower and upper middle-income countries in our sample. The only exceptions to this rule are some high-income countries that specialize in new 4.0 technology and are not main exporters of capital goods. They most likely built a solid manufacturing base in previous decades.

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1. The Oxford dictionary defines the term *internet of things (IoT)* as '[t]he interconnection via the Internet of computing devices embedded in everyday objects, enabling them to send and receive data.'
2. In this study, Frey and Osborne (2017) refer to the term *computerization* as 'job automation by means of computer-controlled equipment.' (p. 2)
3. It is important to note that this claim is formulated on the basis of a hypothetical argument: in order to make such a claim, research on how Industry 4.0 changes the concept and organization of value chains would be needed.
4. Triadic patents are a series of corresponding patents filed at the European Patent Office (EPO), the United States Patent and Trademark Office (USPTO) and the Japan Patent Office (JPO) for the same invention, by the same applicant or inventor (OECD 2005).
5. See the EQuIP website at http://www.equip-project.org for more information.
6. IDR (2020) put forward a methodology to identify Industry 4.0 patents and traded goods. The focus is on four technologies: CAD-CAM, robotics, machine learning and additive manufacturing. Not only do they identify patents that can be associated with these

technologies, they also look at trade statistics and identify those goods that can be associated with three of the above technologies: CAD-CAM, robotics and additive manufacturing (see Appendix F for a more detailed classification of Industry 4.0 goods). Other technologies typically related to Industry 4.0 (such as big data, cloud computing and machine learning) are not considered, since the most important part of these technologies is software, which can hardly be found in the trade classification.

7. In the automotive industry, advances in robotic technologies allow manufacturers to gradually automate a series of production tasks since the introduction of the first industrial robot in the 1960s. It does not come as a surprise that routine and repetitive tasks like welding and painting are now attended to by pre-programmed robotic arms without much human intervention during the production process. It is evident that operative workers can be reskilled and reinstated to deal with more complex tasks. For example, previously, inspection-related tasks could only be dealt with by highly trained inspectors. With the aid of robotic vision technology, reskilled workers can now carry out inspection tasks without compromising quality. Automation in manufacturing has decreased production costs and reduced the price of manufactured goods. This pushes demand towards larger volume and may create more formal sector jobs.

8. An industrial robot is defined by the International Federation of Robotics (IFR 2019) as 'an automatically controlled, reprogrammable, multi-purpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications'; see (ISO 8373) standard obtained from https://ifr.org/industrial-robots.

9. One question often raised by researchers is why we have not seen any response to these new technologies in terms of productivity improvements, since productivity itself has remained rather stagnant over time in aggregate terms. This is indeed an active field of academic research. While some (Gal et al. 2019, among others) emphasize the stronger divide *across* firms between a small set of incredibly innovative and dynamic firms and a larger share of less adaptive firms, others (Esfahani, Fernald, and Hobijn 2019, among others) emphasize that productivity aggregates have simply bounced back from a phase of acceleration during the first IT revolution. It goes beyond the scope of this EQuIP tool to offer further insights into this lively academic debate.

10. Consider, for example, cleaner production, higher working standards, etc.

11. For the remainder of this study, the term 'productivity' refers to labour productivity as defined in the methodology part of this tool. Conceding that labour productivity is only one form for capturing the efficiency of production processes, the focus on this fairly simple variable is retained in a straightforward and—in terms of data coverage—broad measure.

12. Information and communications technology (ICT) builds on the concept of information technology (IT) to emphasize the important or amplified communications integration of (tele)-communication devices such as telephone lines, wireless signals and computers etc., as well as the necessary enterprise software, middle ware, storage, and audio-visual systems that enable users-access to store, transition and manipulate information.

13. As noted before, this successful integration is a very onerous and challenging path and depends on many dimensions and in particular on the successful implementation of necessary prerequisites and capabilities, all of which are discussed in great detail in EQuIP TOOL 9: Industrial Capabilities Indicators.

14. Conversely, let us assume that the majority of workers have already been replaced by robots. In such a scenario, it would be nonsensical to continue speaking about the 'high risk' of robotization.

15. Assume that no workers were being replaced by robots in a particular industry. While this does not imply that there will not be such a scenario in the future, the immediate risk of a worker losing his/her job to a robot may still be considered comparably low.

16. See Keller (2004), Comin and Hobijn (2004) or Ferrier, Reyes and Zhu (2016) for discussions on technology diffusion and the newest UNIDO Industrial Development Report (Cantore 2019) on firm-level analysis of technology adoption.

17. For successful adoption of these production technologies and the establishment of a state-of-the-art manufacturing base in a country, a strong foundation of prerequisites and capabilities is necessary (see EQuIP Tool 9 for a discussion on capabilities).

18. The y axis is not linear, so the ticks are not equidistant. This means larger values are denser on the upper part of the axis. A flat line in the upper part of the figure would be much steeper in a linear version of the axis.

19. Conversely, a levelling out of the robot intensity growth rate at around zero with a robot stock significantly lower than that of more advanced countries would allow identification of cases in which the technology gap between leading economies and developing ones has increased to a degree from which industrial up-scaling has become practically unfeasible (Mayer 2018).

20. A reduction of the growth rate of robot intensity could also be attributable to a replacement of robots by other robots: imagine two old robots were replaced by a more modern and capable counterpart while employment remains unchanged. This would result in a negative growth rate of robot intensity. Alternatively, a positive growth rate of robot intensity does not automatically imply a reduction of employment. In this case, consider a positive growth rate for the number of robots as well as for employment. If the growth rate of robots, however, is higher than that of the number of employees, the growth rate of robot intensity would still be positive.

21. Value added per capita and the employment-to-population ratio can be calculated as $Value\ added\ per\ capita = \frac{Value\ added}{population}$ and $Employment - to - population\ ratio = \frac{Employment}{population}$, respectively.

22. Please note that this is equivalent to calculating $Productivity = \frac{Value\ added\ per\ capita}{Employment}$ as the population term in the nominator and denominator cancels out.

23. In some cases, it might also make sense to combine certain income groups for a more comprehensive view. We illustrate this point by selectively reporting results for the set of 'lower income' countries that are an aggregate of lower middle-income as well as low-income countries. Please see the table's footnotes for more information.

24. For the sake of brevity ,the relevant table is not shown separately. The relevant information is, however, contained in Table 6.4 as part of the in-depth runner industry analysis.

25. This is an important fact to consider as the mean (average) of a sequence of numbers is sensitive to outliers, in other words, it can increase (decrease) considerably if one of the values is very large (small) relative to the other ones.

26. Conversely, a negatively skewed distribution (histogram) has a longer left tail (has more lower values).

27. As the availability of some missing values for runners especially in Viet Nam is attributable the lack of IIP data, the shares of runners are calculated by using runners' value added and total manufacturing value added based on available data only. In other words, the corresponding industry shares are only constructed on the basis of an artificially aggregated manufacturing sector grounded on all available industry-level data series. However, the results are still very representative because the available industry data still represent about 85 per cent and nearly 100 per cent of total manufacturing value added in Morocco and Viet Nam.

28. Percentiles calculated in terms of rankings: $(1-\frac{41}{57} \approx 26\%)$ and $(1-\frac{56}{57} \approx 2\%)$ for value added and employment, respectively.

29. Please note that UNIDO's INDSTAT database is subject to continuous revision. Consequently, the example provided in this section may at some point be based on an updated/revised data set.

30. Please note that in Table I.1, the analysis is conducted 'by capital goods group', i.e. the rows sum up to 100 per cent which is why the measure of 90 per cent cannot be recovered from the presented table.