CEAMeS Discussion Paper Series

CEAMeS Discussion Paper No. 15/2018

The Middle-Income Trap 2.0: The Increasing Role of Human Capital in the Age of Automation and Implications for Developing Asia

Linda Glawe & Helmut Wagner
(University of Hagen)

Center for East Asia Macro-economic Studies [CEAMeS]
University of Hagen

Universitätsstr. 11, 58084 Hagen, Germany

Also distributed as SSRN Paper No. 3263458

The Middle-Income Trap 2.0: The Increasing Role of Human Capital in the Age of Automation and Implications for Developing Asia

Linda Glawe[a] and Helmut Wagner[b]

Abstract. In our paper, we modify the concept of the middle-income trap (MIT) against the background of the Fourth Industrial Revolution and the (future) challenges of automation (creating the concept of the "MIT 2.0"). In particular, we analyze the impacts of automation, artificial intelligence, and digitalization on the growth drivers of middle-income countries and the MIT mechanism. We show that automation reduces the initial growth push for developing countries and leads to an earlier MIT at the lower end of the middle-income range. In addition, once wages start rising, the necessary shift in the growth strategy (from an export-manufacturing based to an innovation-productivity based growth model) is afflicted with higher requirements, particularly regarding human capital. This in turn, will lead to a higher persistence of the trap and it will become more difficult to break out of it. Thus, the MIT 2.0 will be much more challenging than today's "normal" MIT. Our findings suggest that improving human capital accumulation, particularly the upgrading of skills needed with the rapid advance of automation, will be key success factors for overcoming the MIT 2.0. Against this background, we elaborate the implications for developing Asia regarding their probability to experience an MIT 2.0 (with a special focus on human capital as well as higher cognitive and information communication technology skills).

Keywords: automation, AI, human capital, middle-income trap, developing Asia, economic development, economic growth, employment

JEL Classification: J24, O10, O11, O15, O33, O47, O53

[a, b] University of Hagen, Faculty of Economics, Chair of Macroeconomics, 58084 Hagen, Germany, phone +4923319872640, fax +492331987391, e-mail linda.glawe@fernuni-hagen.de and helmut.wagner@fernuni-hagen.de

1 Introduction

Over the last decades, East Asia has seen one of the most remarkable economic success stories and has gained increasing importance in the world economy. The “East Asian Miracle” started with the rise of the Japanese economy in the 1960s/1970s which was soon followed by the so-called four “Asian Tigers” (namely Hong Kong, South Korea, Singapore, and Taiwan). Only one decade later, in the mid-1980s, various members of the Association of Southeast Asian Nations (ASEAN) (especially Malaysia and Thailand) reported rising growth rates. China presents probably the most recent (and famous) success story with reaching even double-digit growth rates over an extended period. The literature agrees that the (initial) key success factors of the East Asian growth model are the combination of a strong domestic export-manufacturing sector as well as specific policy measures to attract foreign direct investment (FDI).

However, more recently, the optimism regarding the (economic) future of East Asian countries has cooled down. Instead, there are growing concerns that China and other (East) Asian middle-income countries (MICs) could become victims of the so-called “middle-income trap” (MIT), a term that refers to the often-observed case of a developing country’s growth rate decreasing significantly when it reaches the middle-income range (MIR) (see Glawe and Wagner, 2016, 2017b). A key question is whether the (East) Asian MICs will be able to follow the Asian success countries by managing a timely shift from the export-manufacturing driven growth strategy to an innovation-productivity driven growth strategy. The MIT literature suggests that key factors to overcome the MIT and successfully accomplish the change in the growth strategy are human capital accumulation, export sophistication, and total factor productivity (see the meta-analysis in Glawe and Wagner, 2017a).

A recent development appears to put additional pressure on the East Asian model and on the future growth of East Asian MICs: The upcoming literature on digitalization, automation, and artificial intelligence (AI) agrees that particularly low-income countries (LICs) and lower-middle-income countries (LMICs) will be negatively affected by the so-called Fourth Industrial Revolution (Schwab, 2017) (see, e.g., World Bank, 2016, and Frey et al., 2016). One key argument is that future technological progress associated with automation and AI will be even more skilled-biased and that the LICs and LMICs are not prepared to cope with the increasing skill requirements, leading to a growing so-called “mismatch between technology and skills” (Acemoglu and Restrepo, 2018). East Asian MICs could be particularly concerned as the Fourth Industrial Revolution will have strong negative implications on the export-manufacturing growth strategy.

We argue that the Fourth Industrial Revolution is strongly intertwined with the pillars of the MIT concept and that the challenges of automation will pose additional difficulties for MICs to overcome the MIR in a timely manner. In order to catch up to the Asian Tigers, the Asian developing countries have to be prepared for this automation-augmented “*MIT 2.0*”.

In our paper, we modify the concept of the MIT against the background of the (future) challenges of automation and the Fourth Industrial Revolution (creating the concept of the MIT 2.0). We analyze the impacts of automation, AI, and digitalization on the growth drivers of MICs and the MIT mechanism. Moreover, we elaborate the implications for developing Asia regarding their probability to experience an MIT on the basis of these modified challenges. Our findings suggest that improving human capital accumulation, particularly the upgrading of skills needed with the rapid advance of automation (such as cognitive and information communication technology (ICT) skills), will be key success factors for overcoming the MIT 2.0.

The rest of the paper is structured as follows: Section 2 presents a brief literature review on the middle-income trap concept and the current literature of automation in the context of the Fourth Industrial Revolution. In Section 3, we then discuss how automation will affect the mechanisms of the MIT. Against this background, Section 4 then analyzes the situation in developing Asia, especially in the (South) East Asian region, with a special focus on human capital as well as higher cognitive and ICT skills. Section 5 concludes.

2 Related literature

The following two sub-sections are devoted to a brief discussion of the literature related to our paper, namely the literature on automation, robots, and AI (in Sub-section 2.1) and the literature on the MIT (in Sub-section 2.2). For extensive surveys on the MIT concept see Agénor (2016) as well as Glawe and Wagner (2016, 2017a). Regarding the automation, digitalization, robot, and AI literature, comprehensive literature overviews are provided, among others, by Autor (2015a), Deutsche Bundesbank Research (2018), Vermeulen et al. (2018), Chapters 2.1 and 2.3, and Dutz et al. (2018), Appendix B.

2.1 Automation, robots, and AI literature

Over the last two decades, path-breaking developments in AI and robotics and the associated accelerated automation of tasks typically performed by human workers have created growing fears that in the future, (human) labor will be made redundant (see, e.g. Brynjolfsson and McAfee, 2011; 2014; Akst, 2013; Autor, 2015a). While the academic literature related to the developments of this so-called "Fourth Industrial Revolution" is still relatively new (see, e.g., Deutsche Bundesbank Research, 2018, p. 2), the fear that technological change has negative impacts on employment has a long history dating back to the early 19th century (for detailed summaries of the history of automation see Autor, 2014, 2015b). An early example includes the Luddites, a radical group of English textile workers who destroyed labor-saving machines as a protest against the automation of the textile production because they feared rising unemployment (see also Dutz et al., 2018, pp. 3-4). In the following century, this automation anxiety has recurred periodically: In 1930, Keynes warned of "technological unemployment". Two decades later, Leontief predicted that "labor will become less and less important" and that "more and more workers will be replaced by machines" (Leontief, 1952). In 1965, Robert Heilbroner argued that due to the ongoing substitution of workers by machines, "human labor itself […] is gradually rendered redundant" (quoted in Akst, 2013). However, all the fears that technological progress and automation would create an unemployment crisis have proven groundless: Advancements in labor-saving machines in the textile industry did not result in long-term unemployment during the First Industrial Revolution; in fact, automation over the 19th century has raised productivity and lowered unemployment since the job creation effect far offset the labor-saving effect of automation (cf. Vivarelli, 2014; Bessen, 2015; Deloitte, 2015; Alexopoulus and Chohen, 2016). Also the recurring fears of increasing unemployment in the 1950s and 1960s did not become reality. The main question that arises is: Will the

Fourth Industrial Revolution be different (cf. Deutsche Bundesbank Research, 2018, p. 1)? One key difference compared to the previous industrial revolutions is that the tasks executed by machines are becoming more complex and that the rise of AI will also increasingly affect (routine) white-collar jobs (see World Economic Forum, 2016; Schireson and Nguyen-Huu, 2017).

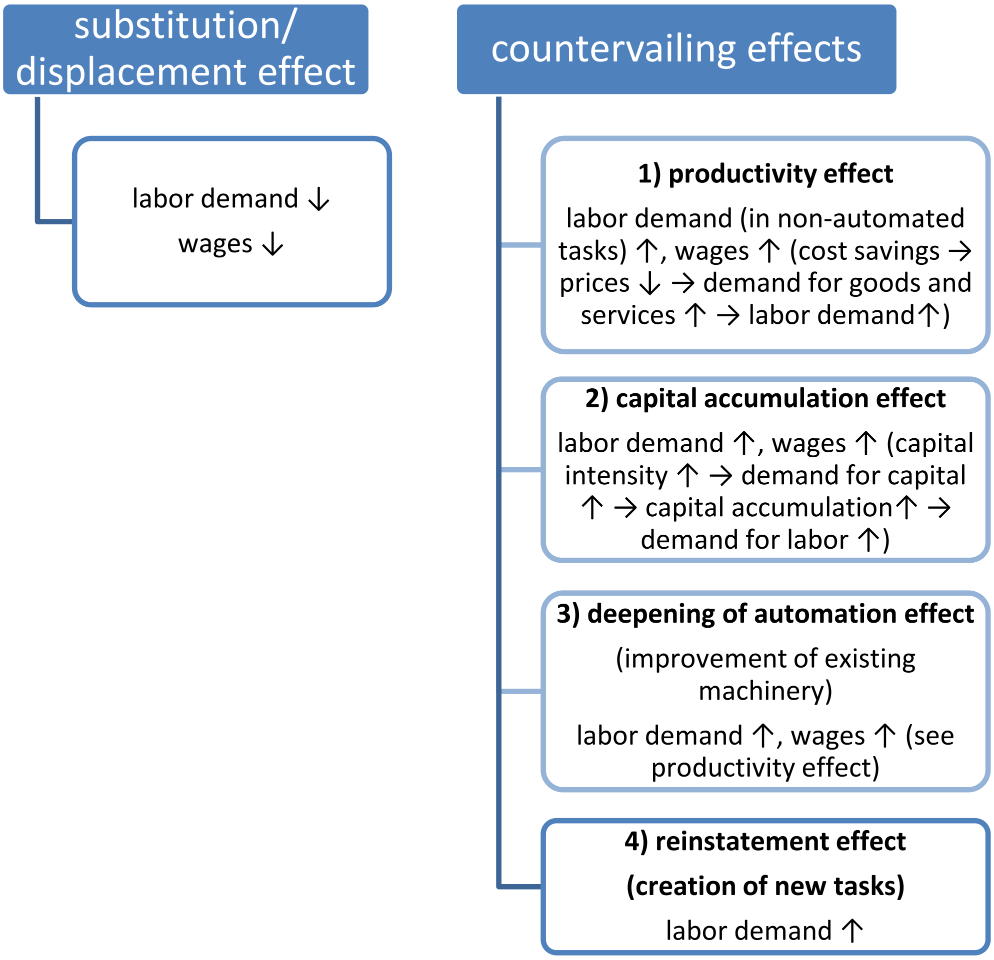
There is consensus among researchers that the Fourth Industrial Revolution will have huge economic and social-politic consequences and will also reshape our understanding as human beings in general – to put it in the words of Schwab (2017), the Fourth Industrial Revolution "will change not only what we do but also who we are". However, no one knows exactly how the Fourth Industrial Revolution will actually unfold.

Partly building upon the experiences of the previous industrial revolutions, the recent literature suggests that the main effects of the current wave of automation on the demand for labor, wages, and employment are the following[1]: Automation induces a *substitution* or *displacement effect* since jobs previously performed by workers are becoming automated, thus reducing the demand for labor and wages. This negative effect is counteracted by various other effects, most importantly the *productivity effect*, the *capital accumulation effect*, the *deepening of automation effect*, and the *reinstatement effect* (see, e.g., Brynjolfsson and McAfee, 2011; Frey and Osborne, 2017; Acemolgu and Restrepo, 2016, 2017, 2018). Figure 1 gives an overview on the various effects of automation.

The productivity effect that results from the cost reductions through automation allows for lower prices and thus induces increases in the demand for goods and services, leading to an increase in the demand for labor. The capital accumulation effect as well as the deepening of automation effect (referring to improvements of tasks that have already been automated) complement the productivity effect and further increase the labor demand. However, Acemolgu and Restrepo (2018) argue that these three countervailing effects alone are not enough to overcome the negative effects that arise due to the substitution of labor by machines since the output per worker increases more strongly than wages and thus, the labor share in national income is reduced. Only the reinstatement effect, that is, the creation of new tasks in areas where humans have a comparative advantage, will be able to compensate the displacement effect (see Acemolgu and Restrepo, 2018, p. 32; an example of job creation in firms whose production process includes the use of AI is provided by Accenture PLC, 2017).

[1] The following discussion is heavily based on the theoretical model developed by Acemolgu and Restrepo (2018) and the discussion in Vermeulen et al. (2018), Section 2.1.

Figure 1. The effects of automation on the demand for labor, wages, and employment.



Source: Own representation based on the model of Acemoglu and Restrepo (2018).

Another interesting question is which jobs will be affected most by automation. Acemoglu and Autor (2011, pp. 1076-1078) distinguish between four occupations based on the skill requirements. In particular they distinguish between occupations that require…

a) **routine tasks** that are **cognitive skill intensive**
(e.g., bookkeepers, proofreaders, clerks)

b) **routine tasks** that are **manual skill intensive**
(e.g., machine operators, cashiers, typists)

c) **non-routine** tasks that are **cognitive skill intensive**
(e.g., researchers, teachers, managers)

d) **non-routine** tasks that are **manual skill intensive**
(e.g., cleaners, hairdressers, street vendors)[2]

[2] The examples are taken from the World Bank (2016, p. 148).

While the jobs of workers in occupations a) and b) can be easily automated, the workers of occupation c) can profit greatly from automation since their jobs are likely to be complemented by technological advances. Workers in occupation d) are not directly affected by automation. Overall, automation leads to a shrinking share of middle-skilled employment and rising shares of high-skilled and low-skilled employment and thus to a “hollowing out” or polarization of the labor market. Vermeulen et al. (2018, p. 3) add that this development is accompanied by fiercer competition and wage stagnations particularly for middle and lower skilled jobs. Overall, labor market polarization can lead to greater income inequality within countries (see also World Bank, 2016, p. 118, see also Section 3.2 of this paper).

2.2 Middle-income trap literature

After having briefly examined the (labor demand and employment structure) effects of digitalization, automation, and AI in the course of the Fourth Industrial Revolution in Sub-section 2.1, we now turn to another relatively new phenomenon: Over the last decade, the term ‘middle-income trap’ (MIT), introduced by Gill and Kharas in 2007, has received much attention in scientific and non-scientific literature. It refers to the often-observed case that a developing country’s growth rate decreases significantly when the country reaches the MIR (Glawe and Wagner, 2016). More precisely, it can be distinguished between absolute and relative empirical definitions of the MIT. The absolute definitions are based on absolute middle-income thresholds and interpret the MIT as a prolonged growth slowdown at the MIR. In contrast, the relative definitions refer to the per capita income relative to the US (or another developed country) and usually interpret the MIT as a failed catching-up process to the advanced high-income countries. As argued among others by Agénor (2016) and Glawe and Wagner (2016, 2017a), the empirical definitions are afflicted with several problems, such as GDP data discrepancy across databases and different versions of databases and differing definitions of the MIR.

From a geographical standpoint, many MIT studies focus on Asian and Latin American countries. Moreover, due to the recent growth slowdown of the Chinese economy, special attention has been paid to the question of whether China is also a potential MIT candidate (see Glawe and Wagner, 2016, 2017a).

Besides the growth model of Agénor and Canuto (2015) and the country specific models of Dabús et al. (2016) and Glawe and Wagner (2017b), focusing on the Argentinian and the Chinese economy, respectively, the MIT literature so far has been largely empirical. According to the meta-analysis of Glawe and Wagner (2017a), the main empirical triggering factors identified by the empirical studies are the export structure, total factor productivity, and human capital.

3 Automation and implications for the MIT

In this section, we analyze the effects of automation on the mechanisms of the MIT. In Sub-section 3.1, we first examine the impacts of an accelerated automation on the growth drivers of developing countries and emerging market economies (EMEs) and discuss the implications for the possibility of a growth slowdown at the MIR. In Sub-section 3.2, we then turn to the point at which EMEs are usually confronted with a change of growth strategy from an export-manufacturing driven growth model to an innovation-productivity based growth model (in order to overcome an MIT) and discuss the increasing challenges due to automation.

3.1 Impacts of automation on the growth drivers of developing countries and EMEs

Structural change and trade/imitation are the two main growth drivers of developing countries. If these initial growth drivers become exhausted and there is no timely shift to an innovation based growth strategy, countries may become stuck in an MIT. Advances in AI, robotics and an accelerated automation will have important implications for these two growth drivers in the sense that they generally weaken their positive effects and make them become exhausted more quickly.

The first growth pillar of developing countries is related to the ***structural change*** process. In particular, the reallocation of labor from the agricultural to the manufacturing sector usually induces strong productivity gains (Lewis, 1954). However, due to the extensive use of advanced machinery, the manufacturing sector is becoming less labor-intensive even in LICs and MICs (Frey et al., 2016). This development implies that development countries are running out of industrialization opportunities sooner and at a lower level of per capita GDP than the early industrializers. This phenomenon is typically referred to as "premature deindustrialization", a term coined by Rodrik (2016). A recent McKinsey study finds that although the manufacturing sector is already one of the most highly automated industries, there is still significant potential for further automation. In particular, the study reveals that the automation potential in the manufacturing sector amounts to 60%, being the second highest value of all industries, only surpassed by accommodation and food services with an automation potential of 73% (McKinsey, 2017, p. 7). Thus, in the future, automation will very likely even further reduce the growth opportunities implied by structural change. For current LICs and LMICs this means that shifting the labor force from the agricultural sector to the manufacturing sector will not create the same rapid growth as experienced by the Asian Tigers and Japan.

The second growth pillar of developing countries is related to (international) ***trade*** and ***imitation***. In particular, specialization in labor-intensive, low-wage tasks and goods according to a country's comparative advantage as well as the imitation of foreign technologies (of advanced countries) generate high transitory growth at an early development stage of an economy (cf. the literature on neo-classical trade and also leader–follower models such as Barro and Sala-i-Martin 1997). However, as automation is becoming less costly, more and more advanced countries will reconsider whether it is still worthwhile to offshore labor-intensive jobs to developing countries and EMEs or whether it is more advantageous to automate them and "bring production home" (Frey et al., 2016, pp. 18, 21-22; Lewis, 2014). A current example of this so-called "re-shoring" trend (Deutsche Bundesbank Research, 2018, p. 1) – sometimes also referred to as "onshoring", "insourcing" or "botsourcing" – include Tesla Motors who now builds its electric cars entirely in the US (Lewis, 2014).[3] Other US companies that started to relocate (part of) their productions back to their home country include Apple, General Elec-

[3] Online available at: https://spectrum.ieee.org/robotics/robotics-software/from-outsourcing-to-botsourcing

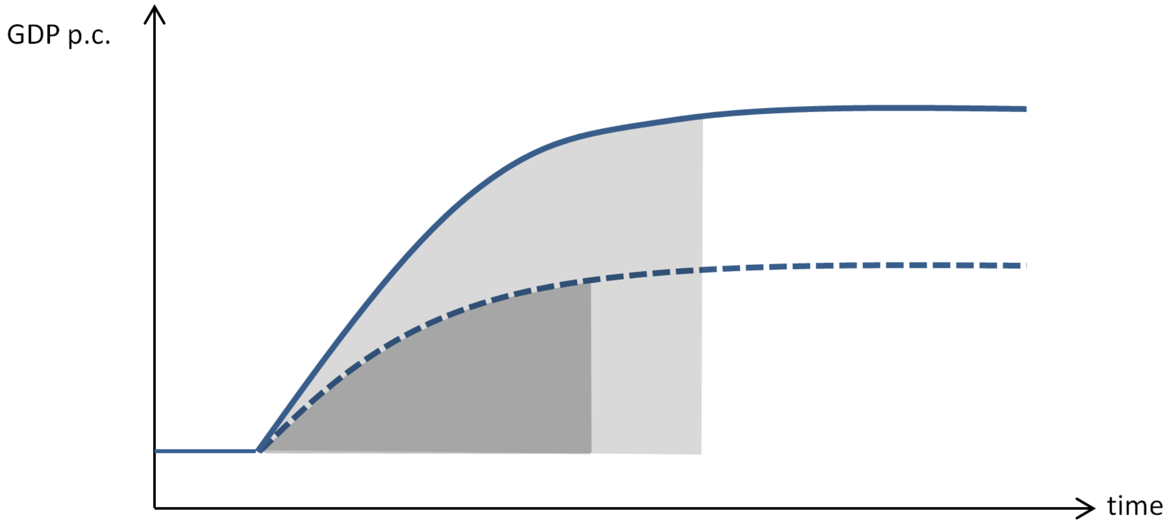
tric, Whirlpool, Otis, and Wham-O.[4] This development is not only restricted to the US; another prominent example is China's domestically shifting supply chain and declining use of foreign intermediate value added as inputs in exports (Frey et al., 2016, pp. 20-21). That means, in the future, developing countries will not only compete with other developing countries but also increasingly with advanced countries which will remain competitive locations due to the possibilities offered by automation. These developments will have negative impacts on the export opportunities of developing countries and EMEs. In addition, developing countries that lack a comparative advantage in manufacturing will become importers of manufacturing and start to "import deindustrialization" from advanced economies due to the relative price decline of manufacturing in advanced high-income countries (Rodrik, 2016, pp. 4, 26), thus reinforcing the "premature deindustrialization" trend described in the previous paragraph. In order to cope with these increasing challenges, EMEs need to diversify their export baskets and move up the value chain so that they can compete with advanced countries. Moreover, they have to succeed in moving to higher productivity services. Both measures, in turn, require a workforce that possesses the necessary education and skills.

Regarding the imitation argument, since fewer companies of advanced economies will engage in trade with developing countries but prefer to locate production facilities closer to their home countries, it will become more difficult for developing countries to internalize technological/knowledge spillover effects that arise through international trade and FDI (see the standard literature on spillovers via the trade channel, e.g. Grossman and Helpman, 1991; Coe et al., 1995; Coe and Helpman, 1995). Moreover, since technology is becoming more and more advanced, it will get harder to copy: As implied by the standard literature on trade spillover effects, an adequate level of human capital is necessary for the successful internalization of technological spillovers. Otherwise, they cannot unfold their positive effect on the domestic productivity (see also Ali et al., 2015). This also affects FDI spillovers, which are another key factor in the East Asian growth strategy (for an overview on the spillover effects via FDI see, e.g., Keller, 2010). (Further) Advances in AI and robotics will require an even higher level of human capital to allow the positive effects of these spillovers to unfold in developing countries and EMEs. These countries often even lack basic education such as literacy and a skill upgrade will require (a) time and (b) a favorable policy and institutional environment.

Overall we have shown that automation is likely to limit the positive effects of both of these two growth sources (structural change and trade/imitation). In particular, the initial growth push implied by an export-manufacturing growth strategy will be smaller and shorter for the current developing countries than for those of the previous generation. This implies that the MIT would occur at the lower end of the MIR, giving rise to a development of the GDP per capita as depicted by the dashed line in Figure 2.

[4] See Forbes (07.12.2012), online at: (https://www.forbes.com/sites/stevedenning/2012/12/07/why-apple-and-ge-are-bringing-manufacturing-back/).

Figure 2. Initial growth push with and without accelerated automation.



Note: The solid line depicts the GDP per capita of a 'normal' MIT country over time, whereas the dotted line depicts the GDP per capita of an MIT country that is additionally confronted with an accelerated automation. The initial growth push (illustrated by the dark grey shaded area) for the latter is much smaller than the initial push of a 'normal' MIT country (represented by the entire grey shaded area) in both, its magnitude and duration.

3.2 Automation and implications for the change in growth strategy of EMEs

So far, we have mainly focused on the impact of automation on the initial drivers of developing countries. However, the MIT mechanism has other bottlenecks skeptical to automation. Once the initial growth drivers disappear, that is, there is no more possibility to shift additional workforce into the manufacturing sector, wages begin to rise (see Glawe and Wagner, 2016, p. 527 and also Sub-section 3.1 of this paper). According to the MIT literature, this is the critical point where an EME has to manage a change in its growth strategy. In the context of automation, this development (rising wages) also removes an important restriction of automation in developing countries since labor-saving automation is not economically feasible if cheap labor is abundant (or the price for capital is relatively low, see Habakkuk, 1962). According to the World Bank Development Report (2016), two-thirds of all jobs in developing countries are susceptible to automation. However, besides low wages, there is still another important factor that slows down the automation process in developing countries, namely the slower technological adaption, resulting in adaption time lags (World Bank, 2016, pp. 22-23). Taking this time lag into account, the share of employment that can be automated and computerized declines, however, it is still relatively high, e.g. 55.42% for China, 51.88% for Thailand, and 48.77% for Malaysia (see World Bank, 2016, p. 23).

In Section 2.1, we have already in detailed explained the various effects of automation and technological advances in robotics and AI. Among others, we have shown that technological change is skill-biased (favoring high-skilled workers). In particular, non-routine, high cognitive tasks benefit from automation, while routine tasks (both, cognitive and manual) can easily be automated. Non-routine manual tasks are largely unaffected by automation. That is, workers whose jobs have been substituted by machines can (a) change to the non-routine cognitive occupation jobs (if they have the necessary skills, see also below), (b) change to the non-routine manual occupation jobs that are usually low productivity jobs in the service sector, or (c) lose their jobs permanently (so-called "technological joblessness"), meaning that substitution effect of automation outpaces the job creation effect through complementarities.[5]

Option (a) requires a skill adjustment process since these jobs usually require non-routine, higher-order cognitive skills and technical skills, especially ICT skills (World Bank, 2016, p. 123). The skill adjustment process is already an ambitious task for advanced economies and thus poses an even greater challenge for developing countries and EMEs that in general have a much lower level of education and even lack foundational cognitive skills (such as literacy and basic math). Human capital/Education is also a key triggering factor identified by the general MIT literature (Glawe and Wagner, 2017a). However, in the context of automation, human capital accumulation and education will experience an enormous rise in importance for overcoming an MIT since the required levels increase substantially (and will further increase).

Option (b) does not require such advanced skills as Option (a) but would lead to a higher unproductive service sector share and thus reinforce the Baumol's cost disease phenomenon. Hence, aggregate productivity and growth will decline (see Wagner, 2013, 2018). Moreover, since productivity is a key factor for overcoming the MIT, this development would pose a hindrance of catching-up to the advanced countries and thus increase the probability of an MIT.

The greater the degree of skills and technology mismatch, the less likely will Option (a) be, and thus lead to either long-term joblessness or an increase in employment in the unproductive service sector (Option (b)), which, in turn, intensifies the growth slowdown at the MIR and increases its persistence. Thus, a timely adaption of the educational system to the requirements of automation, particularly the development of ICT skills, will be a key factor for developing countries and EMEs to avoid a prolonged growth slowdown. Since this process requires time, today's LICs should already start to implement such a skill-upgrading strategy (which is of course not easy due to the often instable political environment in these countries).

Overall, automation and the resulting skill-technology mismatch will lead to a higher degree of persistence of the growth slowdown at the MIR. Moreover, following a skill-upgrading- and human capital-intensifying growth strategy to mitigate this tendency will cause enormous challenges for EMEs which see themselves confronted with much higher educational requirements than the EMEs of the previous generation. In sum, the breaking out of sluggish growth and the return to the catching up path will have a high human capital threshold/barrier.

Another chain of argumentation also has important implications for the MIT mechanism: As we have discussed above, automation will increase the number of high-skilled workers that work in non-routine cognitive occupation jobs and low-skilled jobs in the service sector while middle-skilled jobs will disappear (Ford, 2015; Autor et al., 2003; Levy and Murnane, 2007). This development will result in a labor market polarization (or "hollowing out", see World Bank, 2016, p. 21 and Sections 2.1 and 3.1 of this paper) and rising inequali-

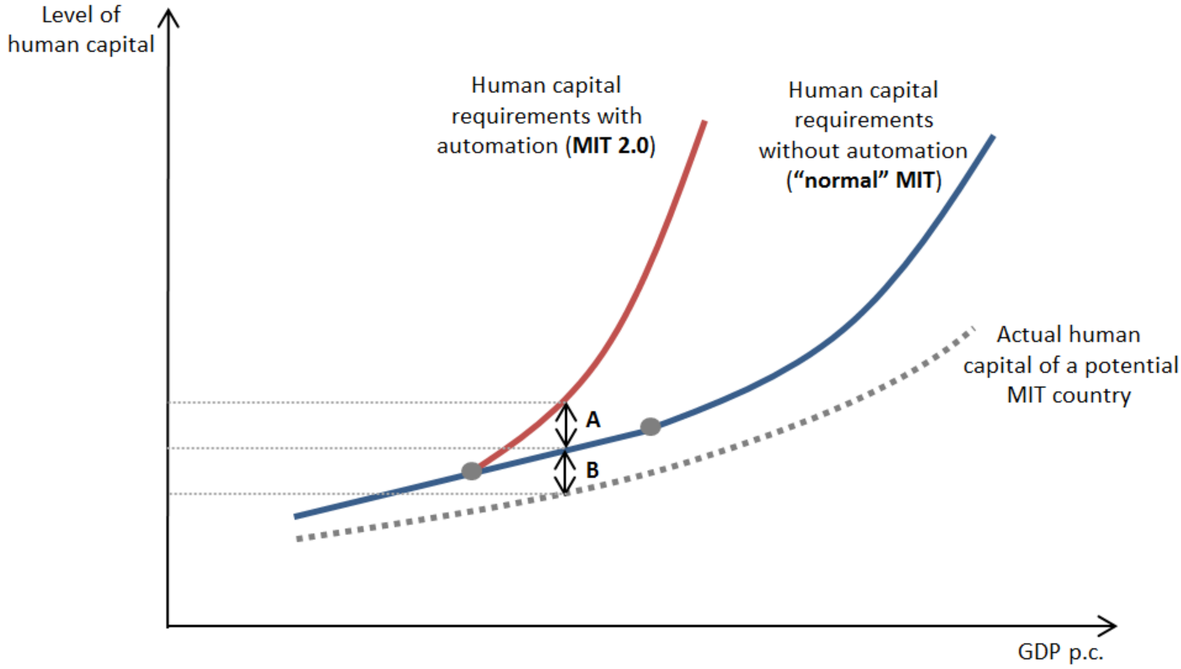
[5] Of course, the successful realization of Options (a) and (b) also usually imply a short-term unemployment due to the skill and job searching adjustment process eventually necessary skill adjustment process.

ty, which is also an MIT triggering factor (see Glawe and Wagner, 2017a; a comprehensive overview on the relationship between inequality and the MIT is provided by Islam, 2015). The argumentation is the following: When wages start to rise, a country has to focus on exporting more sophisticated goods. Since product development is costly and requires time, an EME needs a strong domestic market. However, inequality actually results in a limited home market for technological sophisticated goods and thus puts a critical constraint on the export sophistication (see also Islam, 2015, pp. 6-7 and Kharas and Kohli, 2011, pp. 284-286). Increasing the overall level of human capital (according to the skill requirements of automation) could help to mitigate the problem of rising inequality that arises through automation. Again, education and human capital have a key role for coping with the challenges of the MIT 2.0

In Sub-section 3.1 and 3.2 we have shown that automation affects the MIT mechanism at two main stages: First, the typical initial growth drivers (structural change and trade/imitation) are weakened. That is, automation reduces the initial growth push for developing countries and leads to an earlier MIT at the lower end of the MIR. Second, once wages start rising, the necessary shift in the growth strategy (from an export-manufacturing based to an innovation-technological based growth model) is afflicted with higher requirements, particularly regarding human capital. This in turn, will lead to a higher persistence of the trap and it will become more difficult to break out of it. Thus, the MIT 2.0 will be much more challenging than today's "normal" MIT. In all points where automation is strongly intertwined with the MIT mechanism, human capital, particularly the presence of non-routine cognitive (ICT) skills, is a critical constraint. Although "education/human capital" is also an important triggering factor identified by the general MIT literature, automation will further increase its importance and will put it in the center of the MIT 2.0.

Figure 3 summarizes in how far the human capital/skill requirements to overcome an MIT change via automation: The thick lines illustrate the human capital requirement curves, that is, they represent the skill and human capital level (at different income stages) that is needed to successfully overcome the MIT. The blue line presents the requirement curve in the usual environment of MIT countries (without accelerated automation), whereas the red line presents the requirement curve for an environment characterized by accelerated automation (MIT 2.0). The grey dotted line denotes the actual skill level of a typical developing country (and later EME). As implied by the above discussion, the skill requirements in the presence of an accelerated/intensified automation are not only in general higher (due to the skill-biased character of technological change that accompanies automation), expressed in the steeper increase of the MIT 2.0 skill requirement curve, but since the typical growth drivers already disappear at lower levels of development than before, the MIT 2.0 requirement curve takes-off earlier than the normal MIT requirement curve. We can see that the gap/vertical distance between the actual curve and the requirement curve of the MIT 2.0 (distance A+B) is much higher than that between the actual curve and the "normal MIT" requirement curve (only distance B), illustrating that it will become by far more difficult to upgrade the workforce to successfully overcome the MIT 2.0.

Figure 3. Increased skill requirements due to automation.



4 Implications for developing Asia

In Section 4 we analyze in how far the Asian countries are prepared to cope with the increasing challenges associated with the catching up process in an increasingly automated world/environment. We will focus particularly on East Asian, South East Asian, and South Asian countries. In the following, when speaking of "East Asian" countries, we mean both, East Asian countries and South East Asian countries. Moreover, we refer to the group of East Asian, South East Asian, and South Asian countries as "Asian countries".

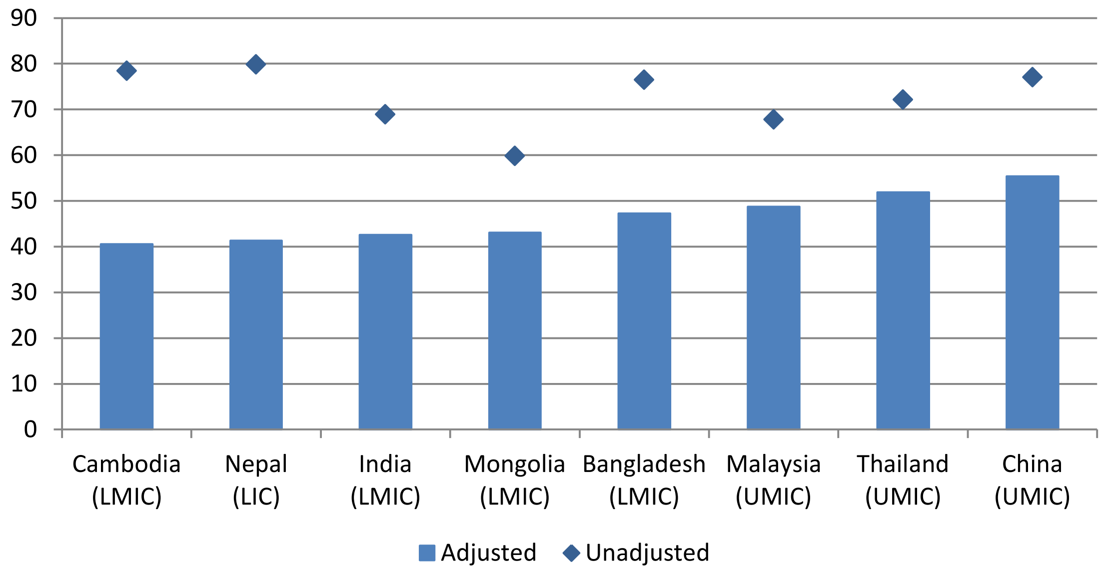
Since our analysis of Section 3 revealed that human capital is the most important key factor for overcoming the automation-augmented "MIT 2.0", in the following, we focus especially on indicators related to human capital and skill upgrading.[6] We take a look at (i) the general educational situation, in particular at the percentage of the population with secondary and tertiary education (in Sub-section 4.1), (ii) the percentage of the workforce that works in occupations that require non-routine cognitive and interpersonal skills (in Sub-section 4.2), as well as (iii) an ICT development (IDI) index (in Sub-section 4.3). Finally, Sub-section 4.4 briefly summarizes our main findings and elaborates on which Asian countries are most susceptible to falling into an MIT 2.0.

We focus particularly on the performance of LICs and LMICs since they will be most affected by the MIT 2.0. However, since there are only few LICs in East Asia, South East Asia and South Asia, the main part of the analysis is related to LMICs. Moreover, we also briefly discuss the development of the Asian upper-middle income countries (UMICs) to compare them with the LMIC group.

[6] This focus on human capital is also supported by the general theoretical literature on automation, in particular by Kattan et al. (2018). The authors develop an overlapping-generations model in which education quality can determine whether automation is beneficial or detrimental.

Before we start our analysis, we take a brief look at the estimated share of employment that is susceptible to automation in various Asian countries. There are two common indicators for the technical automation potential of the economy: Figure 4 depicts an index compiled by the World Bank (2016) and Figure 5 presents an alternative index developed by McKinsey (2017). It has to be noted that the World Bank (2016) actually provides two measures of automation potential, the "adjusted automation potential" and the "unadjusted automation potential", respectively. The former uses adjusted probabilities based on the adoption time lag of earlier technologies (Comin and Mestieri 2013) to take into account that the technology adoption in poorer countries follows a slower pace, while the latter uses unadjusted probabilities from Frey and Osborne (2013).[7]

Figure 4. Adjusted and unadjusted automation potential (World Bank 2016).



Data Source: World Bank (2016). *Notes:* "LIC" stands for low-income country, "MIC" for middle-income country, "LMIC" for lower-middle-income country, "UMIC" for upper-middle-income country, and "HIC" for high income country. We refer to the income thresholds of the most recent 2017 World Bank classification.

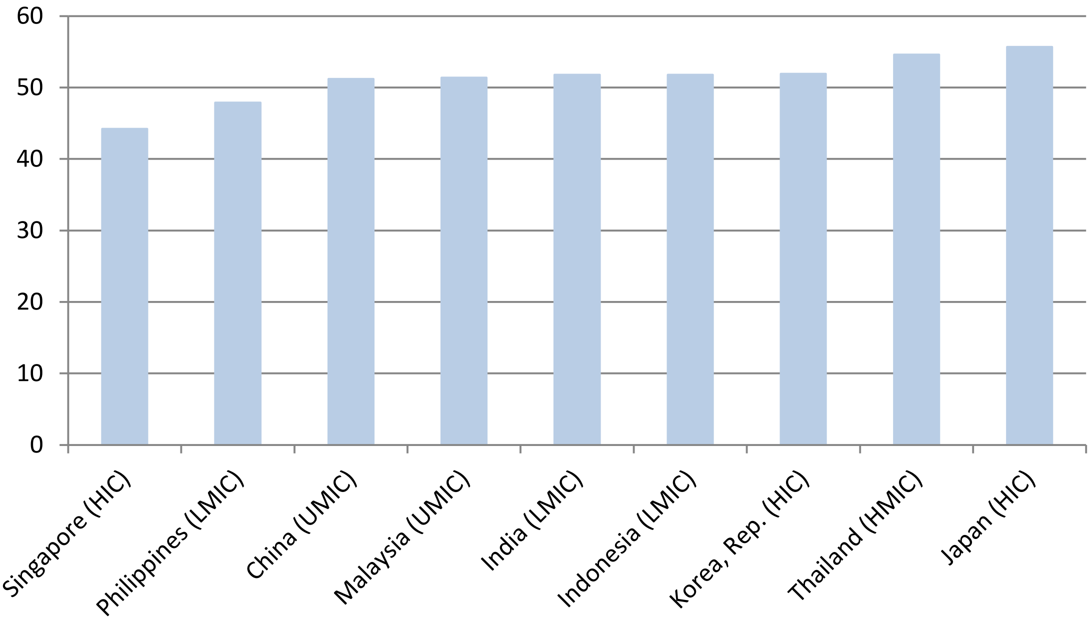
In Figure 4, the unadjusted index is depicted by the dark blue diamonds and the adjusted index (on which we will focus primarily in the rest of this section) is illustrated by the blue bars. We can see that the automation potential is the highest among the Asian UMICs, namely 48.77% for Malaysia, 51.88% for Thailand, and 55.42% for China. Bangladesh is the LMIC with the highest automation potential in the sample (47.27%), followed by Mongolia and India with both around 43%. The automation potential is lowest in Cambodia and Nepal (in both countries around 41%), however, the unadjusted automation potential of the latter two countries is significantly higher (around 80%) and thus exceeds all other values of our

[7] Besides these general studies, there are also some region-specific studies. For example, Chang and Huynh (2016) estimate the percentage of workers in occupations at high risk of automation in the ASEAN-5 countries. They find that 56% of the jobs in the ASEAN-5 countries face a high risk of automation (p. 13). In general, their estimates are in line with those of the two studies listed above. In contrast, the ADB (2015) report, focusing on the (South) East Asian and South Asian region, finds a considerably lower proportion of workers at risk of automation; however, these estimates constitute an exception within the empirical automation literature.

sample. Overall, in all LICs and LMICs in our sample, the adjusted automation potential is above 40%, the unadjusted values vary between 60% and 80%.

Unfortunately, the McKinsey (2017) study does not cover the same countries as the World Bank (2016) study, however, it therefore provides also data for various East Asian HICs, and two other LMICs, namely Indonesia and the Philippines. For the countries that are covered by both studies, there is a broadly similar trend (if we refer to the adjusted index) with the exception that India's automation potential is much higher according to the McKinsey (2017) estimations (about 9.22 percentage points). In the McKinsey (2017) sample, there is no clear trend that UMICs have on average a higher automation potential, and besides the Philippines, all LMICs report an automation potential above 50%.

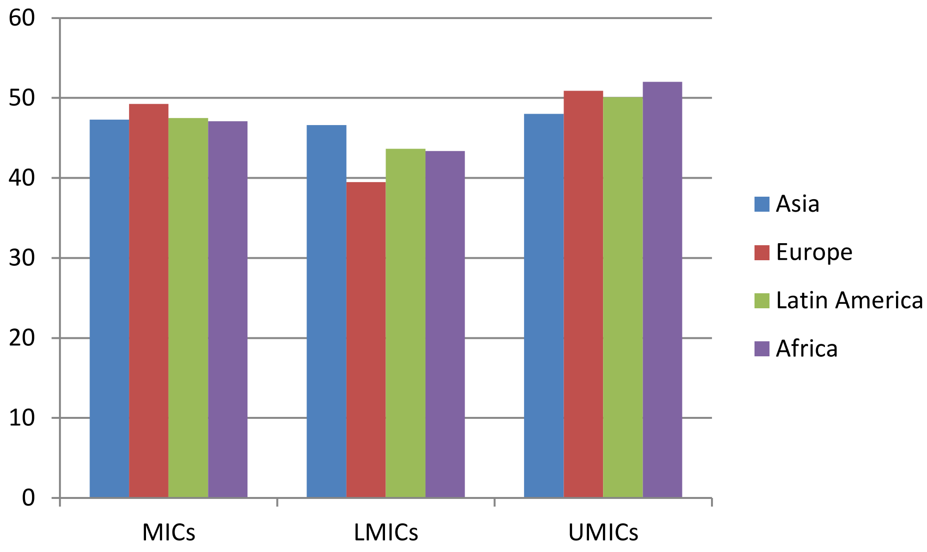
Figure 5. Adjusted and unadjusted automation potential (McKinsey 2017).



Data Source: McKinsey (2017). *Notes:* "LIC" stands for low-income country, "MIC" for middle-income country, "LMIC" for lower-middle-income country, "UMIC" for upper-middle-income country, and "HIC" for high income country. We refer to the income thresholds of the most recent 2017 World Bank classification.

How does the situation look in international comparison? Figure 6 depicts the averages of the adjusted automation potential of MICs, LMICs, and UMICs in Asia (East Asia, Southeast Asia, and South Asia), Europe, Latin America, and Africa. We can state that MICs in all countries face a relatively similar automation potential, ranging between 47.07% (for Latin American MICs) and 49.27% (for European MICs). If we further distinguish between LMICs and UMICs, the Asian LMICs have the highest automation potential while the Asian HMICs have the smallest automation potential (compared to the other regional LMIC and HMIC groups). Moreover, the Asian LMICs and Asian UMICs have a relatively similar level of automation potential (with a gap of only 1.42 percentage points), while the gap is much greater for the other continent groups (11.40 for Europe, 8.65 for Africa and 6.43 for Latin America). This implies that the Asian LMICs – and thus possible MIT 2.0 candidates – will be confronted with a (slightly) more comprehensive automation than the LMICs of the other regional groups.

Figure 6. Automation potential in regional comparison (World Bank 2016 data).



Data Source: World Bank (2016). *Notes:* "LIC" stands for low-income country, "MIC" for middle-income country, "LMIC" for lower-middle-income country, "UMIC" for upper-middle-income country, and "HIC" for high income country. We refer to the income thresholds of the most recent 2017 World Bank classification.

After having briefly examined the automation potential in Asia, particularly in (lower) middle-income countries, we now turn to the analysis of various human capital and educational indicators to evaluate the "readiness" of the Asian countries to cope with the increasing human capital and skill requirements.

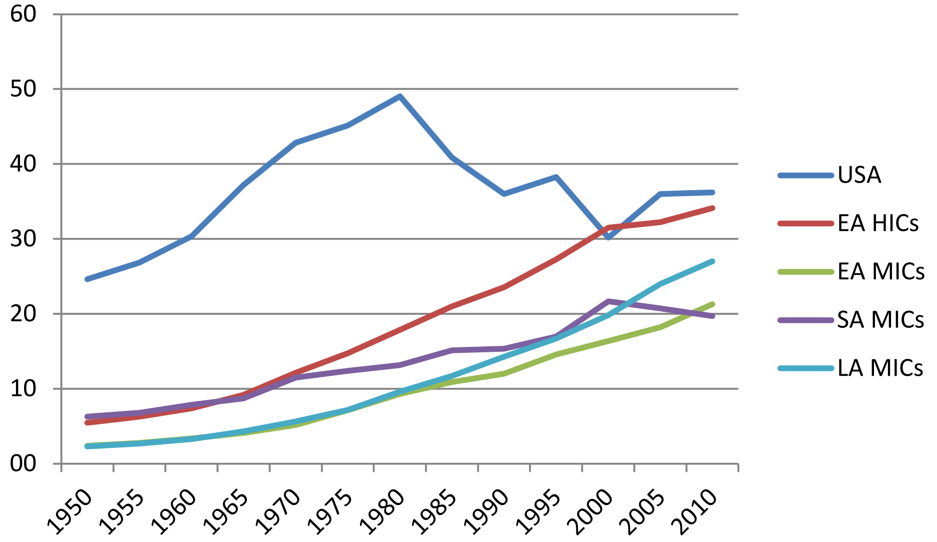
4.1 General educational indicators

In this Sub-section 4.1, we provide an overview of the general educational situation in the Asian countries. We first compare their performance regarding the percentage of the population with completed secondary education and then discuss the development of the respective tertiary education indexes.

Percentage of the population with completed secondary education

As depicted by Figure 7a, Latin American and East Asian MICs both show a catching up tendency to the United States and (since 1995/2000) also to the group of the East Asian HICs. The performance of South Asian MICs was relatively strong prior to 2000, however, they were surpassed by Latin American MICs in 2005 and by East Asian MICs in 2010. Between 2000 and 2010, South Asian MICs even recorded on average a slight decline in the share of population with completed secondary education.

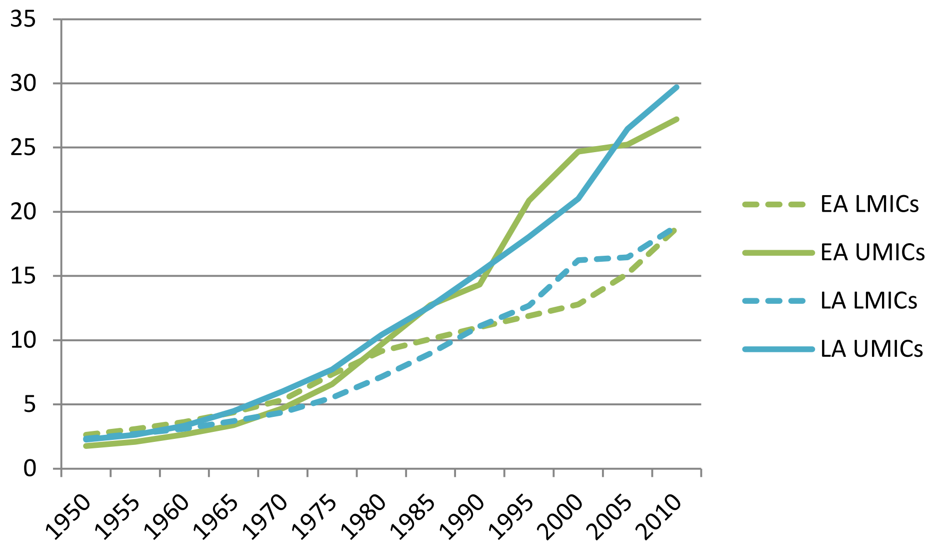
Figure 7 a. % of the population with completed secondary education (MICs).



Data Source: Barro and Lee (2013). *Notes:* "LIC" stands for low-income country, "MIC" for middle-income country, "LMIC" for lower-middle-income country, "UMIC" for upper-middle-income country, and "HIC" for high income country. We refer to the income thresholds of the most recent 2017 World Bank classification. "EA" stands for East Asian and South East Asian countries, "SA" for South Asian countries and "LA" for Latin American countries.

If we compare East Asian and Latin American LMICs and UMICs (in Figure 7b), we can see a relatively similar pattern in both regions. In fact, the stronger catching-up tendency of the Latin American MICs depicted in Figure 7a might stem from the fact that the Latin American MIC group consists of more UMICs (more precisely, 15 UMICs and 5 LMICs) than the East Asian MIC group (only 3 UMICs and 7 LMICs). However, also in Figure 7b, in 2010, Latin America slightly outperforms East Asian LMICs (since 1990) and UMICs (since 2010). It has to be noted, that the increase in the percentage of the population with completed secondary education among the East Asian LMICs has gained momentum since 2000.

Figure 7 b. % of the population with completed secondary education (LMICs, UMICs).

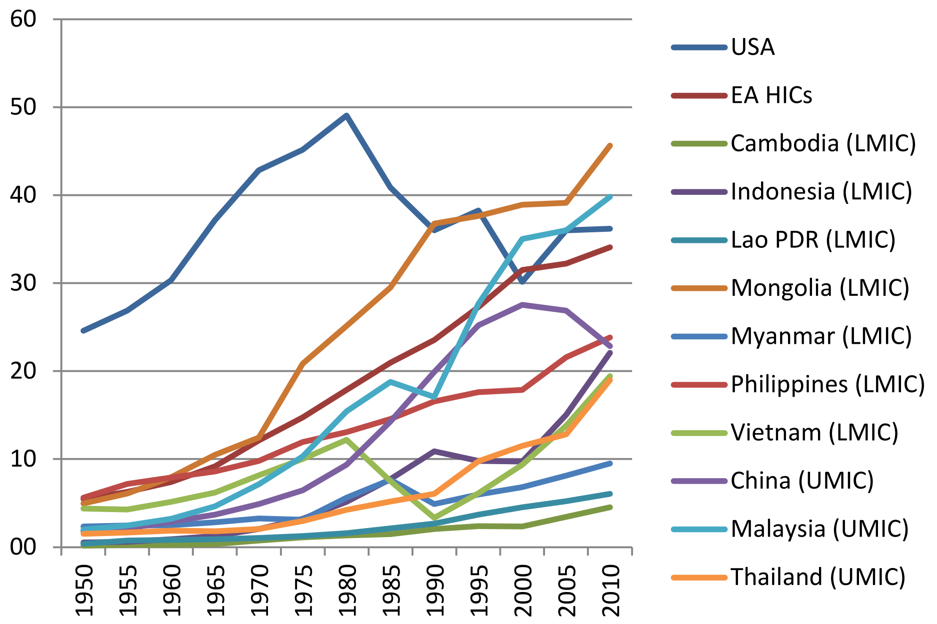


Data Source: Barro and Lee (2013). *Notes:* See notes of Figure 7a.

Figure 7c reveals that at the country level, besides the Chinese downward trend since 2000, all countries show a positive trend and partly strong catching up tendencies. Malaysia performs best among the UMICs, surpassing the East Asian HIC group in 1995. Among the LMICs, the Philippines and Indonesia were able to lower their gap to the East Asian HIC group to only 12.00 and 10.24 percentage points, a massive reduction. Since these LMICs will also be most affected by automation (according to the McKinsey, 2017, study), this strong performance in secondary education is a first (!) good sign that these LMICs will be able to cope with the increasing skill requirements in the future. However, Mongolia's development is the strongest among the LMIC group: In 2010, 45.61% of the population had a completed secondary education (compared to 34.08% for the EA HIC group and 36% for the US). In contrast, the LMICs Cambodia, Laos, and Myanmar recorded the weakest performance among the countries in our sample.

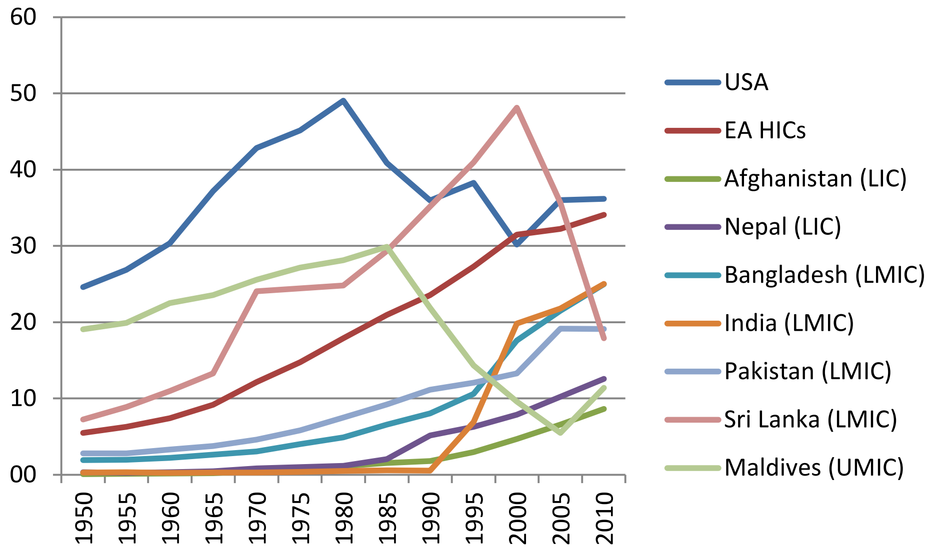
We now turn to the South Asian countries: As illustrated by Figure 7d, India's take off since 1990 is especially remarkable, standing in sharp contrast to the sharp decreases in completed secondary education in Sri Lanka and the Maldives (starting in 2000 and 1985, respectively). But also Bangladesh's catching up path appears promising. Afghanistan records the lowest values of completed secondary education (8.65 in 2010); however, it has also seen constant improvements since 1995.

Figure 7 c. % of the population with completed secondary education – East Asia.



Data Source: Barro and Lee (2013). *Notes:* See notes of Figure 7a.

Figure 7 d. % of the population with completed secondary education – South Asia.



Data Source: Barro and Lee (2013). *Notes:* See notes of Figure 7a.

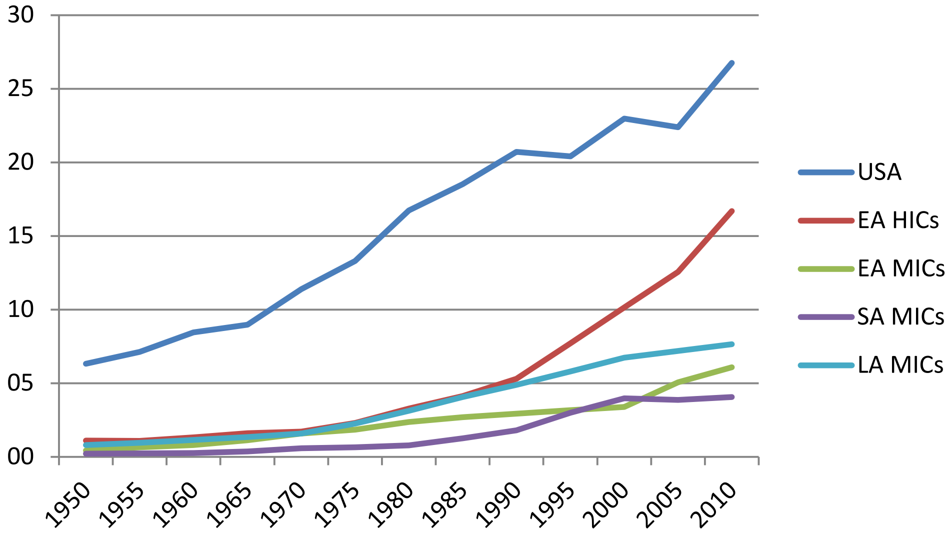
Percentage of the population with completed tertiary education

We now turn to the development of tertiary education, which will be probably even more important than secondary education in a future, more automated world, since tertiary education is usually more strongly associated with the development of higher cognitive skills (see, e.g., OECD, 2005; World Bank, 2012).

Analogous to Figure 7a, Figure 8a depicts the average performance of MICs in East Asia and South Asia. The United States and the East Asian HIC group as well as the Latin American MIC group serve as a benchmark.

We can see that East Asian MICs and South Asian MICs both record on average relatively low levels of (completed) tertiary education. In 2010, the gap to the East Asian HIC group amounted 20.7 percentage points for the East Asian MICs; the gap of the South Asian MICs was even slightly higher. Strikingly, since 2000, the South Asian MICs recorded a stagnating tendency, while the development of the East Asian MICs has gained momentum. Notably, Latin American MICs record on average a higher level of tertiary education, also at the more disaggregated level, that is when distinguishing between LMICs and UMICs (see Figure 8b).

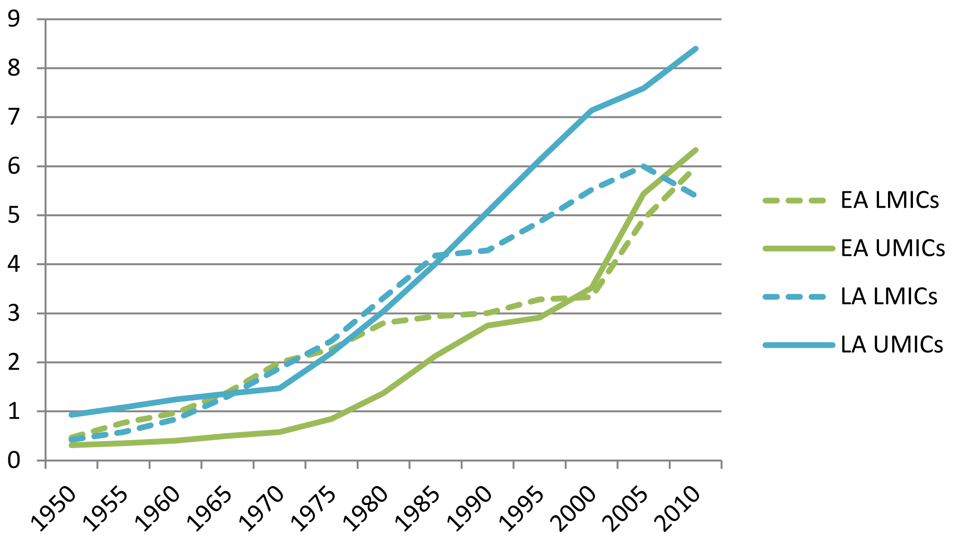
Figure 8 a. % of the population with completed tertiary education (MICs).



Data Source: Barro and Lee (2013). *Notes:* See notes of Figure 7a.

Even the Latin American LMICs have seen higher levels of completed tertiary education than the East Asian UMICs until 2005. Interestingly, Figure 8b reveals that East Asian LMICs and UMICs have relatively similar levels of tertiary education since 2000 and between 1950 and 2000 the East Asian LMICs even outpaced the East Asian UMIC group. Moreover, in 2010, the East Asian LMIC group surpassed the Latin America LMIC group.

Figure 8 b. % of the population with completed tertiary education (LMICs, UMICs).

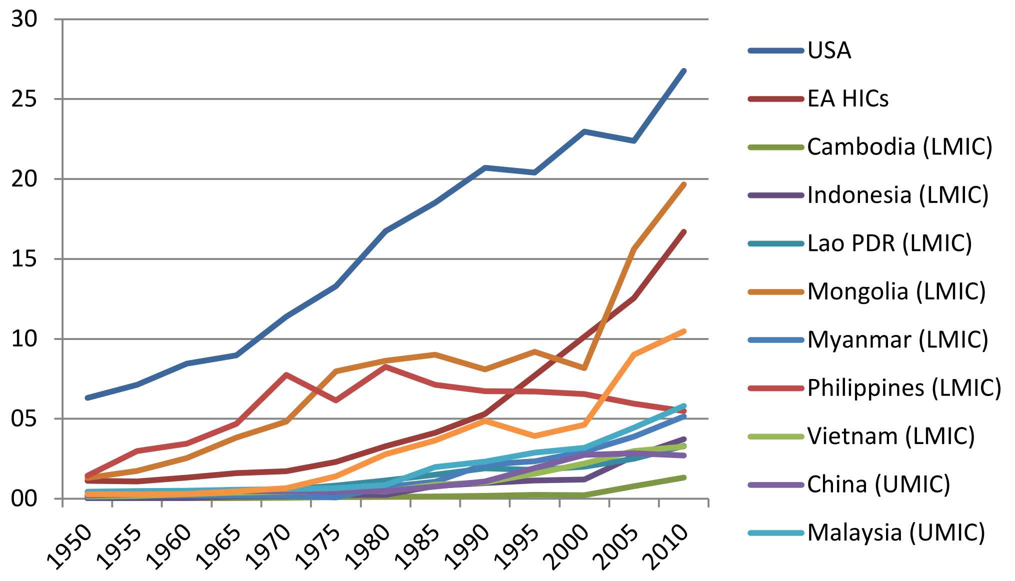


Data Source: Barro and Lee (2013). *Notes:* See notes of Figure 7a.

Figure 8c reveals that among the East Asian LMICs, Mongolia has seen spectacular growth in tertiary education, even surpassing the East Asian HICs in 2005 and 2010. Most other LMICs also report an upward tendency, however at a much lower pace. Only the declining share of population with tertiary education in the Philippines seems to be a bit worrying.

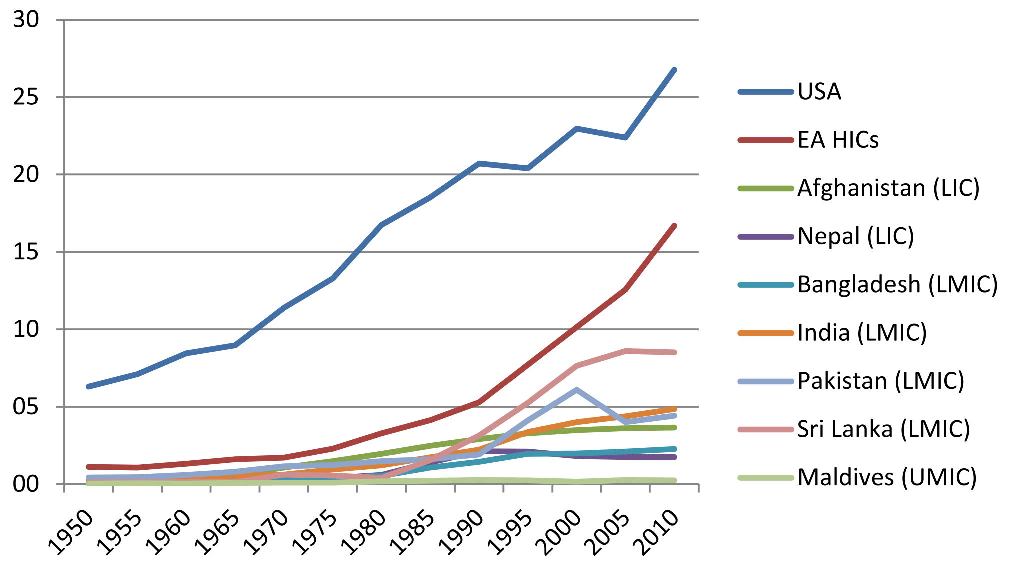
The development of tertiary education is relatively similar across most South Asian countries depicted in Figure 8d, showing a stagnating trend. Worryingly, the only UMIC in the sample (the Maldives) performs worst (in 2010, only 0.25 percentage of the population had a completed tertiary education). Among the LMICs, Sri Lanka showed a catching up tendency between 1980 and 2000, but afterwards, the percentage of the population with completed tertiary education leveled off. Only India has seen constant increases in tertiary education, however, due to the strong performance of the US and East Asian HICs, the gap between India and these countries has actually widened. Overall, the South Asian LMICs have a much weaker performance in tertiary education then the East Asian LMICs.

Figure 8 c. % of the population with completed tertiary education – East Asia.



Data Source: Barro and Lee (2013). *Notes:* See notes of Figure 7a.

Figure 8 d. % of the population with completed tertiary education – South Asia.



Data Source: Barro and Lee (2013). *Notes:* See notes of Figure 7a.

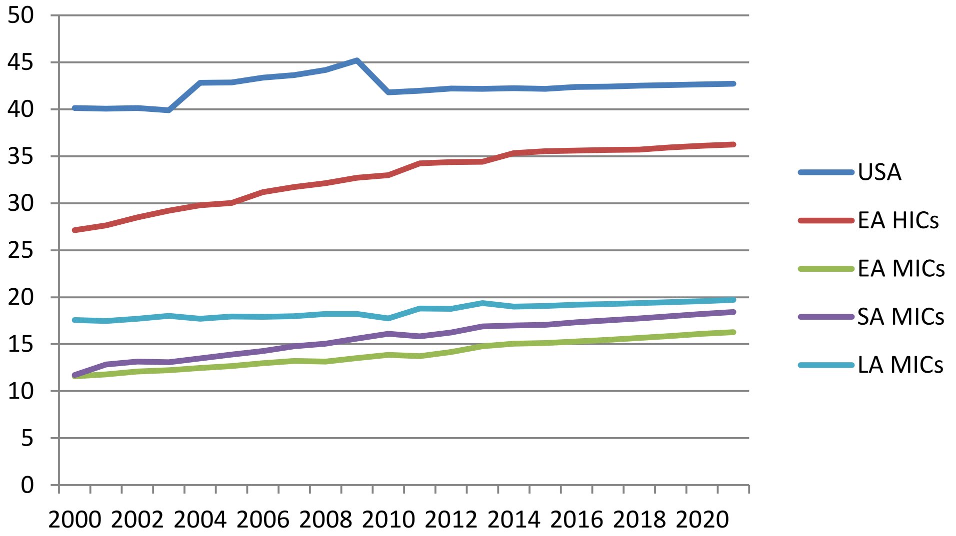
4.2 Percentage of the workforce that works in occupations that require high skills

After having examined the general educational situation in Asia, in this Sub-section 4.2, we focus on the development of the skill level of workers in the Asian countries by using occupational data. As already explained in Sections 2.1 and 3.2, the technological change induced by the Fourth Industrial Revolution is skill-biased, favoring workers with (and occupations that require) advanced (ICT) skills. We first take a look at the employment share in high-skill occupations and then briefly discuss the polarization of the labor market.

The data on employment by occupation is taken from the ILO Laborstat Database; the indicator is available for three groups of occupations (high-skilled, middle-skilled and low-skilled) classified according to major groups as defined in one or more versions of the International Standard Classification of Occupations (ISCO). High-skilled occupations include legislators, senior officials and managers, professionals, and technicians and associate professionals.[8] These occupations require non-routine cognitive and interpersonal skills (see also World Bank, 2016, p. 121) which are usually not substituted but complemented by automation and technological advances, that is technology is labor-augmenting and thus has primarily positive effects on the overall economy (see also Sections 2.1 and 3.2) (Note, however, that in combination with an increasing share of low-skilled occupations and diminishing middle-skilled occupations, this will cause higher inequality which is a hindrance to economic growth in the long run, see also Section 3.2).

Figure 9a shows that East Asian, South Asian, and Latin American MICs all have relatively similar shares of people working in high-skilled occupations, ranging from 13.85% in East Asia to 18.78% in Latin America (in 2015). Interestingly, South Asian MICs record a higher value than the East Asian MICs (namely, 15.85%). According to the ILO Laborstat Forecast and our calculations, in 2021, the employment shares in high-skilled occupations will on average increase to 15.48%, 17.52% and 19.28% for East Asian, South Asian, and Latin American MICs, respectively. This is still far away from the shares predicted for the United States or the East Asian HICs whose employment shares in high-skilled occupations are forecasted to amount to 42.39% and 35.65%, respectively.

Figure 9 a. % of the population working in high-skilled occupations (MICs).

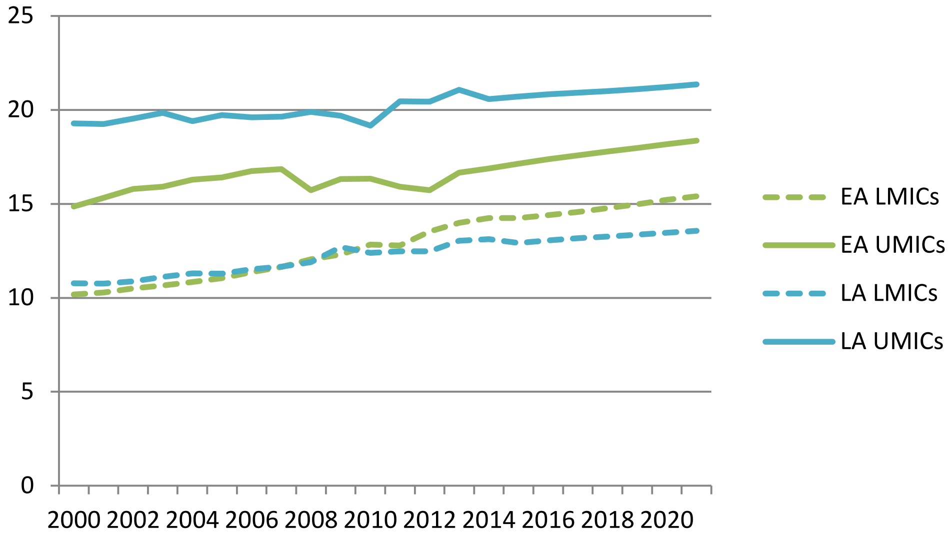


Data Source: ILO Laborstat. *Notes:* See notes of Figure 7a.

[8] A detailed description of the indicator is provided online at: file:///F:/A8-2018-05-29%20MIT%202.0%20Automatization%20HC%20East%20Asia/Data/ILO%20description_OCU_EN.pdf (especially on p. 2).

Figure 9b depicts that while the Latin American UMICs still outperform the East Asian UMICs, the East Asian LMICs have been able to surpass the Latin American LMICs.

Figure 9 b. % of the population working in high-skilled occupations (LMICs, UMICs).

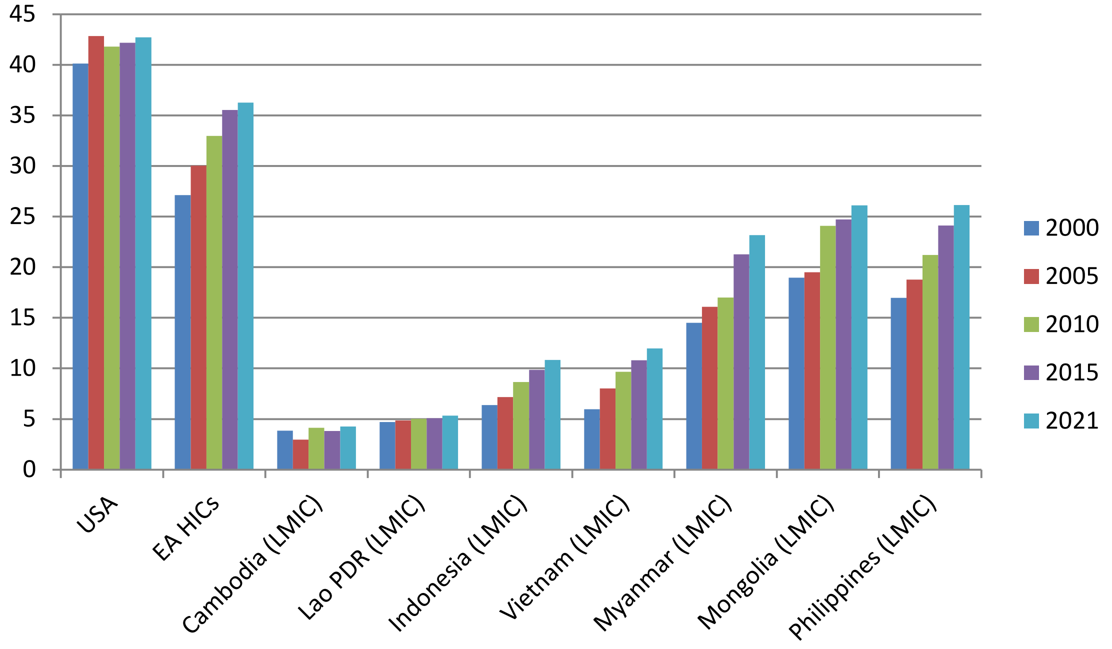


Data Source: ILO Laborstat. *Notes:* See notes of Figure 7a.

At the country level perspective, Figure 9c depicts that the East Asian LMICs have very unequal levels of high-skilled occupation employment shares: Especially Cambodia and Laos record very low values and are only predicted to have minor increases in the following years. The picture is slightly better for Indonesia and Vietnam, which are prospected to have high-skilled occupation labor shares of around 11% and 12% by 2021. Myanmar, Mongolia and the Philippines record the highest values and are also forecasted to have the highest increases between 2015 and 2021 (Myanmar and the Philippines around 2 percentage points).

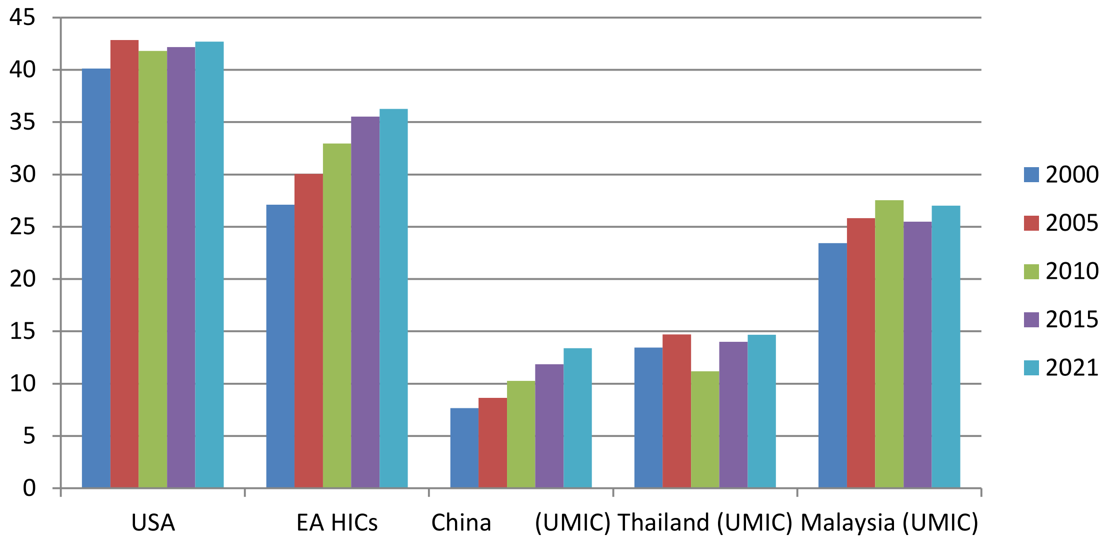
Strikingly, many East Asian LMICs outperform the East Asian UMICs, particularly China and Thailand (see Figure 9d) which will stay under the 15% threshold by 2021 (according to the ILO forecast).

Figure 9 c. % of the population working in high-skilled occupations – East Asia (LMICs).



Data Source: ILO Laborstat. *Notes:* See notes of Figure 7a.

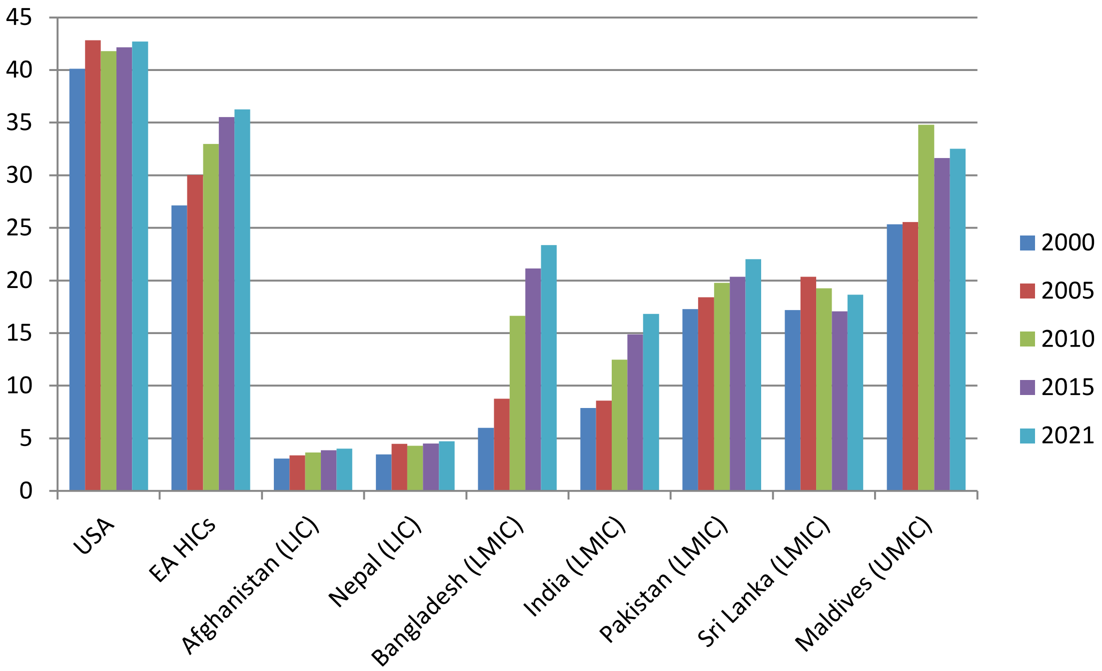
Figure 9 d. % of the population working in high-skilled occupations –East Asia (UMICs).



Data Source: ILO Laborstat. *Notes:* See notes of Figure 7a.

In South Asia, the LICs record very low employment shares in high-skilled occupations and are only expected to see marginal increases in the following years (see Figure 9e). Among the LMICs, Bangladesh and Pakistan record the highest values, but also India has seen strong increases over the last decade, almost reaching the 15% threshold in 2015. Sri Lanka's performance has on average seen declining shares of workers in high-skilled occupations since 2005 and this declining trend is forecasted to continue until 2021.

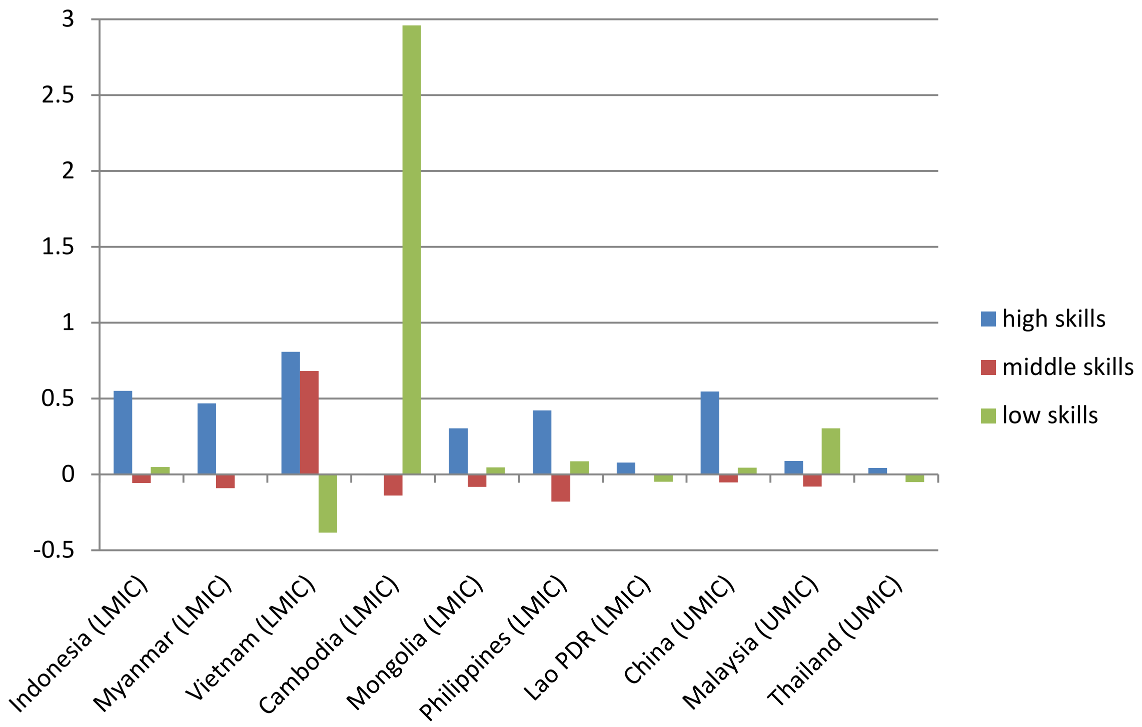
Figure 9 e. % of the population working in high-skilled occupations – South Asia.



Data Source: ILO Laborstat. *Notes:* See notes of Figure 7a.

However, as already mentioned at the beginning of this sub-section, the combination of a higher high-skilled occupation share and also a higher low-skilled occupation share (at the cost of a diminishing middle-skilled occupation class) will polarize the labor force and increase the inequality within a country. The World Bank (2016) Report finds that also developing countries are susceptible to this development. Figures 10a and 10b show the total change in employment shares between 2000 and 2015.

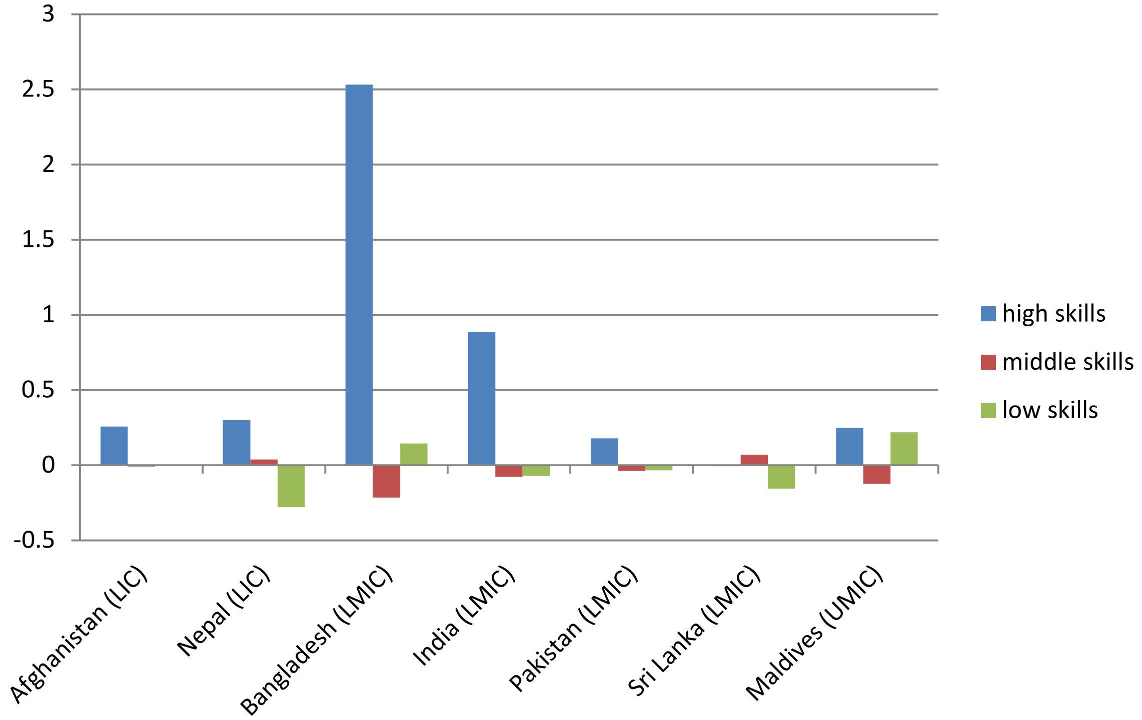
Figure 10 a. Average change in employment shares – East Asia (2000-2015).



Data Source: ILO Laborstat. *Notes:* See notes of Figure 7a.

Figure 10a reveals various employment trends across East Asian LMICs (and UMICs). First, we can see that most East Asian LMICs have experienced increases in the share of the labor force working in high-skilled occupations, especially Vietnam, Indonesia, and Myanmar. Only Cambodia and Laos have seen no or only a very slight increase. (Among the East Asian UMICs, only China shows significant improvements regarding the high-skilled occupational employment share (with an overall increase of slightly more than 0.5%), while Malaysia and Thailand are outperformed by most LMICs.). Second, the employment share in low-skilled occupations in East Asian LMICs has only increased slightly or has even fallen; the major exception of this trend is (again) Cambodia: the country recorded an increase in the share of the labor force working in low-skilled occupations of almost 3%. Finally, in most East Asian LMICs (and all UMICs), the share of the labor force working in middle-skilled occupations declined or stagnated between 2000 and 2015 (Vietnam being the only exception).

Figure 10 b. Average change in employment shares – South Asia (2000-2015).



Data Source: ILO Laborstat. *Notes:* See notes of Figure 7a.

Figure 10d shows that among the South Asian LMICs, India and Bangladesh have seen significant increases in the share of workers in high-skilled occupations (0.89% and even 2.53%, respectively). In most LMICs, the share of low-skilled occupation jobs declined or stagnated, the same is true for the share of middle-skilled occupation jobs.

In sum, over the period from 2000 to 2015, East Asian and South Asian LMICs have on average seen an increase in the employment share in high-skilled occupations, whereas the employment share in middle-skilled occupations decreased (the main exception being Vietnam). Moreover, besides in Cambodia, we cannot state an increasing trend in the employment share in low-skilled occupations, which is in general a positive trend. Among all Asian LMICs, the performance of Vietnam, Bangladesh and India appears to be particularly promising (compared to the other countries in our sample).

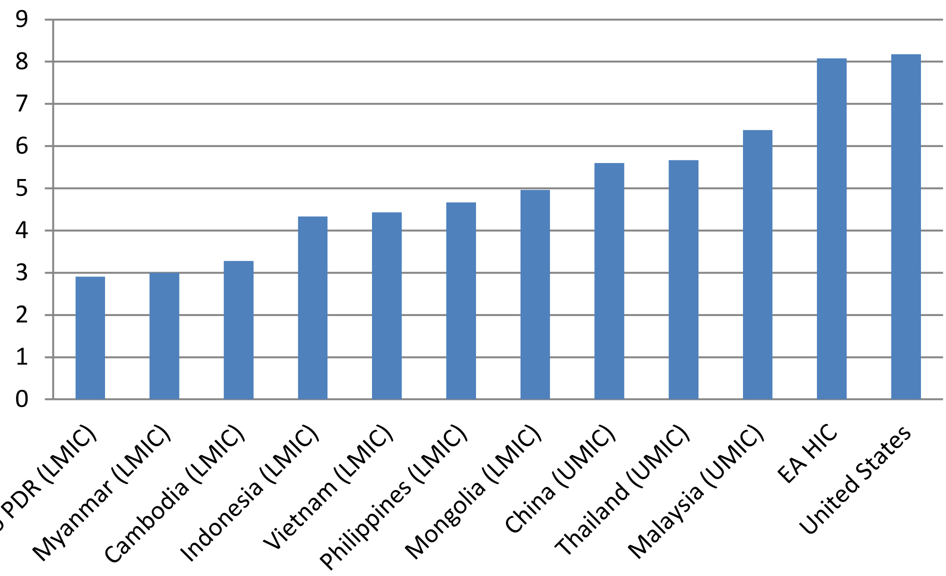
4.3 ICT Development Index (IDI index)

In this Sub-Section 4.3, we focus on the ICT Development Index (IDI). The IDI measures the level of ICT development in a country and is due to the International Telecommunication Union (ITU, 2017). It is a composite index that consists of three sub-indexes (ICT access, ICT use, and ICT skills) as well as eleven indicators on ICT access, use and skills, capturing key aspects of ICT development. In 2017, the worldwide mean IDI amounts to 5.11; the minimum and maximum values are 0.96 and 8.98, respectively.

Figure 11a reveals that the IDI among the East Asian LMICs is lowest in Laos, Myanmar and Cambodia (roughly around 3 for all three countries). Indonesia, Vietnam, and the

Philippines perform slightly better, reaching 54%, 55%, and 58% of the East Asian HIC and United States level. Mongolia is the strongest performer among the East Asian LMICs (with an IDI of 4.96 corresponding to 61% of the East Asian HICs level). The East Asian UMICs record IDIs between 5.60 and 6.38. If we compare the average performance of Latin American MICs and East Asian MICs, the latter group records a slightly higher IDI score (4.92 versus 4.56). Also if we further subdivide into LMICs and UMICs, the East Asian sub-groups outperform their Latin American counterparts (with their average scores being about 9% and 20% higher, respectively).

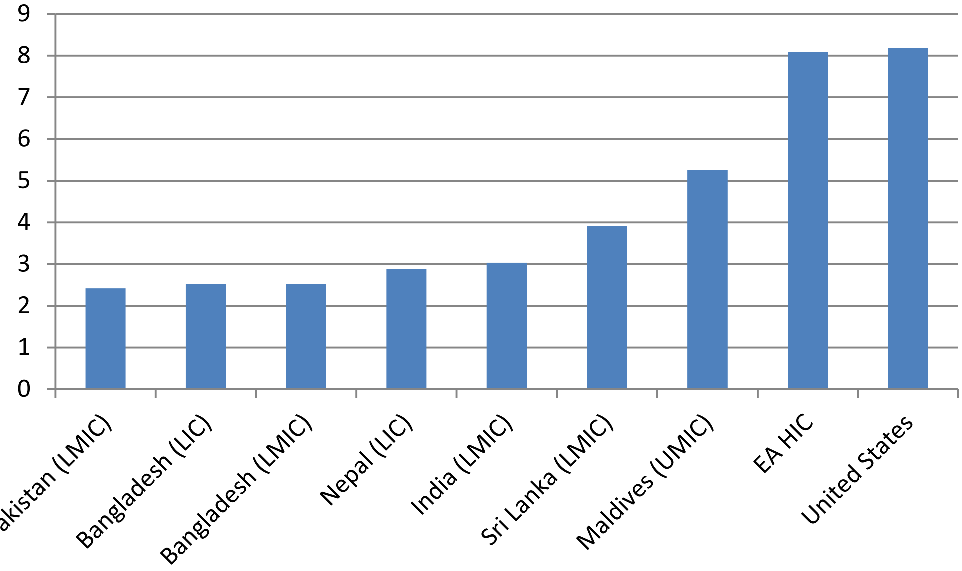
Figure 11 a. IDI – East Asian (MICs).



Data Source: ITU (2017). *Notes:* See notes of Figure 7a.

The performance of the South Asian LMICs is much lower, only Sri Lanka and India surpass the threshold of 3. Also the South Asian LICs report relatively low values, reaching only approximately one third of the level of the United States and the East Asian HICs and are even far below the world average of 5.11. The Maldives, the only UMIC in the South Asian country group, reports an IDI of 5.25, which is slightly below that of the East Asian UMICs; however it is still higher than the Latin American UMICs' average score. In contrast, the South Asian LMICs are outperformed by the Latin American LMICs, which on average report a 22% higher score.

Figure 11 b. IDI – South Asia (MICs).



Data Source: ITU (2017). *Notes:* See notes of Figure 7a.

In sum, the Asian UMICs perform relatively well; however, the low IDIs of almost all South Asian LICs and LMICs in our sample as well as of some East Asian LMICs (in particular, Laos, Myanmar and Cambodia) are a bit worrying. In the future, these countries should focus more on their ICT development in order to keep pace in the ongoing digitalization and automation process.

4.4 Summary of our main findings

Table 1 provides a summary of our key findings. Regarding the secondary and tertiary educational performance, a "+" indicates a positive performance (meaning increasing shares of secondary/tertiary education), a "++" a positive performance in combination with a catching up tendency to the East Asian HIC group or the United States, and "+++" implies a very good performance (very strong catching up or even surpassing the frontier countries). In contrast, a "-" indicates a stagnating performance and a "--" implies a declining tendency. For the last two columns, a "-", "+", "++", and "+++" correspond to an employment share in high-skilled occupations below 5%, between 5% and 15%, between 15% and 25%, and above 25%, respectively, and an IDI below 3, between 3 and 4, between 4 and 5, and over 5, respectively. Of course, this choice of thresholds is partly subjective and shall only provide a general impression of the performance of the Asian (L)MICs in cross-country comparison.

Table 1. Summary – East Asia, South East Asia, South Asia (LMICs, UMICs).

Country	Income Class	Region	Sec Educ	Tert Edu	High Skills	IDI17
Cambodia	LMIC	South East Asia	+	+	-	-
Indonesia	LMIC	South East Asia	++	+	+	+
Laos	LMIC	South East Asia	+	+	-	-
Mongolia	LMIC	East Asia	+++	+++	+++	+
Myanmar	LMIC	South East Asia	+	++	++	-
Philippines	LMIC	South East Asia	++	-	+++	+
Vietnam	LMIC	South East Asia	++	+	+	+
China	UMIC	East Asia	-	-	+	++
Malaysia	UMIC	South East Asia	+++	++	+++	+++
Thailand	UMIC	South East Asia	++	++	+	++
Afghanistan	LIC	South Asia	+	+	-	
Nepal	LIC	South Asia	+	-	-	-
Bangladesh	LMIC	South Asia	++	-	++	-
India	LMIC	South Asia	++	-	+	-
Pakistan	LMIC	South Asia	++	-	++	-
Sri Lanka	LMIC	South Asia	--	-	+	-
Maldives	UMIC	South Asia	-	--	+++	++

Notes: "LIC" stands for low-income country, "MIC" for middle-income country, "LMIC" for lower-middle-income country, "UMIC" for upper-middle-income country and "HIC" for high income country. "Sec Educ" ("Tert Edu") denotes the share of the population (aged 15 or older) with completed secondary (tertiary) education. "High Skills" denotes the employment share in high-skilled occupations and "IDI17" stands for the ICT Development Index for the year 2017.

Among the East Asian and South East Asian LMICs, Mongolia performs best. Regarding various indicators, it even outperforms the East Asian HICs and the United States. Therefore, from the human capital and skill requirement standpoint, it has the lowest probability to experience an "MIT 2.0". Also Myanmar and the Philippines show an overall good performance regarding the human capital and skill indicators. The performance of Cambodia and Laos is most worrying since they record the lowest values in all categories. Among the South Asian LMICs, Bangladesh and Pakistan are the best performing countries; however they both have still relatively low levels of tertiary education. Sri Lanka, and also the two LICs Nepal and Bangladesh bring up the rear. Interestingly, South Asian LMICs perform significantly lower than the East Asian LMICs regarding tertiary education and the IDI.

5 Conclusion

In our paper, we have analyzed how the current and future challenges of automation and the Fourth Industrial Revolution will influence the initial growth drivers of MICs and the MIT mechanism. In particular, we have shown that automation affects the MIT mechanism at two main stages: First, the typical initial growth drivers (structural change and trade/imitation) are weakened and this reduces the initial growth push for developing countries, leading to an earlier MIT at the lower end of the MIR. Second, once wages start rising, the necessary shift in the growth strategy is afflicted with higher requirements, particularly regarding human capital. This in turn, will lead to a higher persistence of the trap and it will become more difficult to break out of it. Thus the automation-augmented “MIT 2.0” will be much more challenging than today’s “normal” MIT. At all points where automation is strongly intertwined with the MIT mechanism, human capital, particularly the presence of non-routine cognitive and ICT skills, is a critical constraint. Thus, improving the skills and knowledge needed with the rapid advance of digitalization, automation and artificial intelligence will be key success factors for overcoming the automation-augmented “MIT 2.0” and for successfully catching up to the advanced countries.

However, of course, the rapid development of human capital alone is no guarantee for success for the emerging countries. As already indicated, human capital is intertwined with various other factors that are also decisive for overcoming a growth slowdown at the middle-income range (see Glawe and Wagner, 2017a, for an overview of these factors). Moreover, country specific characteristics and the institutional-political framework certainly also play a crucial role for the economic success of a developing country or EME.[9] Thus, one should interpret improvements in human capital (in accordance with the requirements of the Forth Industrial Revolution) as a vitally important *necessary* but not sufficient condition to avoid the MIT 2.0.

In the second part of our paper, we particularly analyzed the implications for Asian developing countries and EMEs, especially regarding their skills and their human capital performance. In particular, we focused on the percentage of the population with completed secondary and tertiary education, the share of the population working in occupations that require high cognitive and interpersonal skills, and an ICT development index. Overall, South Asian LMICs perform on average slightly worse than their East Asian counterparts, particularly regarding tertiary education. Among the East Asian LMICs, Mongolia’s performance is outstanding, but also Myanmar and Philippines score well. Among the South Asian LMICs, Bangladesh and Pakistan are the best-performing countries.

Our analysis only gives a first impression of the situation in developing Asia and readiness of the Asian LMICs (and LICs) to cope with the increasing challenges of digitalization and automation. Future research should more extensively analyze the skill requirements and develop indicators that measure cognitive, socioemotional, interpersonal and ICT skills more precisely. Moreover, in depth country studies could provide a more accurate picture of the situation in individual countries.

[9] See, for example, Glawe and Wagner (2017a), Section 4.5 (updated version) and also Wagner (2015). Future research should focus more strongly on the interconnections between human capital, institutional quality, and automation/artificial intelligence.

References

Accenture PLC (2017) How Companies Are Reimagining Business Processes With IT, https://sloanreview.mit.edu/article/will-ai-create-as-many-jobs-as-it-eliminates/.

Acemoglu, D., and Autor, D. (2011) Skills, tasks and technologies: Implications for employment and earnings. *Handbook of Labor Economics* 4: 1043–1171.

Acemoglu, D., and Restrepo, P. (2016) The Race Between Machine and Man: Implications of Technology for Growth, Factor Shares and Employment. NBER Working Paper 22252. Rochester, NY, USA: Social Science Electronic Publishing, Inc.

Acemoglu, D., and Restrepo, P. (2017) Robots and Jobs: Evidence from US Labor Markets. NBER Working Paper 24119. Rochester, NY, USA: Social Science Electronic Publishing, Inc.

Acemoglu, D., and Restrepo, P. (2018) Artificial Intelligence, Automation and Work. NBER Working Paper 24196. Rochester, NY, USA: Social Science Electronic Publishing, Inc.

Agénor, P.-R. (2016) Caught in the Middle? The Economics of Middle-Income Traps. *Journal of Economic Surveys* 31(3): 771-791.

Agénor, P.-R., and Canuto, O. (2015) Middle-Income Growth Traps. *Research in Economics* 69(4): 641–60.

Akst, D. (2013) What Can We Learn From Past Anxiety Over Automation? Wilson Quarterly. Online available at: https://wilsonquarterly.com/quarterly/summer-2014-where-have-all-the-jobs-gone/theres-much-learn-from-past-anxiety-over-automation/.

Alexopoulos, M., and Cohen, J. (2016) The Medium Is the Measure: Technical Change and Employment, 1909–1949. *Review of Economics and Statistics* 98 (4): 792–810.

Ali, M., Cantner, U., and Roy, I. (2015) Knowledge Spillovers through FDI and Trade: Moderating Role of Quality-Adjusted Human Capital. *Journal of Evolutionary Economic* 26(4): 837-868.

Asian Development Bank (ADB) (2015) Key Indicators for Asia and the Pacific, 46th Edition: A smarter future – Skills, education and growth in Asia. Manila: Asian Development Bank.

Autor, D.H. (2014) Polanyi's Paradox and the Shape of Employment Growth. NBER Working Paper 20485. Rochester, NY, USA: Social Science Electronic Publishing, Inc.

Autor, D.H. (2015a) Why Are There Still So Many Jobs? The History and Future of Workplace Automation. *Journal of Economic Perspectives* 29(3): 3–30.

Autor, D.H. (2015b) The Paradox of Abundance: Automation Anxiety Returns. In: Rangan, S. (Ed.), Performance and Progress: Essays on Capitalism, Business, and Society, pp. 237-260. Oxford and New York: Oxford University Press.

Autor, D.H., Levy, F., and Murnane, R.J. (2003) The Skill Content of Recent Technological Change: An Empirical Exploration. *Quarterly Journal of Economics* 118: 1279–1333.

Barro, R. J., and Lee, J.-W. (2013) A New Data Set of Educational Attainment in the World, 1950-2010. *Journal of Development Economics* 104: 184–198.

Barro, R.J. and Sala-i-Martin, X. (1997) Technological Diffusion, Convergence, and Growth. *Journal of Economic Growth* 2(1): 1–26.

Bessen, J. (2015) *Learning by Doing: The Real Connection between Innovation, Wages and Wealth.* New Haven, CT: Yale University Press.

Brynjolfsson, E., and McAfee, A. (2011) *Race Against the Machine: How the Digital Revolutionis Accelerating Innovation, Driving Productivity, and Irreversibly Transforming Employment and the Economy.* Lexington, MA: Digital Frontier Press.

Brynjolfsson, E., and McAfee, A. (2014) *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. New York: W.W. Norton & Company.

Chang, J.-H., and Huynh, P. (2016) *ASEAN in Transformation – The Future of Jobs at Risk of Automation*. Geneva: ILO.

Coe, D.T., Helpman, E., and Hoffmaister, A. (1995) North-South R&D Spillovers. *The Economic Journal* 107(440): 134-149.

Coe, D.T., and Helpman, E. (1995) International R&D spillovers. *European Economic Review* 39(5): 859–887.

Comin, D., and Mestieri, M. (2013) If Technology Has Arrived Everywhere, Why Has Income Diverged? INET Research Note 26, New York: Institute for New Economic Thinking.

Dabús, C., Tohmé, F., and Carabello, M. A. (2016) A Middle Income Trap in a Small Open Economy: Modeling the Argentinian Case. *Economic Modeling* 53: 436-44.

Deloitte (2015) *From Brawn to Brains: The Effect of Technology on Jobs in the UK*. London: Deloitte.

Deutsche Bundesbank Research (2018) Digital Economics – How AI and Robotics Are Changing Our Work and Our Lives. EU Monitor Digital Economy and Structural Change. Frankfurt am Main: Deutsche Bundesbank.

Dutz, M.A., Almeida, R.K., and Packard, T.G. (2018) *The Jobs of Tomorrow – Technology, Productivity, and Prosperity in Latin America and the Caribbean*. Washington, DC: World Bank.

Ford, M. (2015) *The Rise of the Robots: Technology and the Threat of Mass Unemployment.* Oxford, UK: Oneworld Publications.

Frey, C.B., and et al. (2016) *Technology at Work v2.0 – The Future Is Not What It Used to Be*. Citi GPS: Global perspectives & solutions. Online available at: https://www.oxfordmartin.ox.ac.uk/downloads/.../Citi_GPS_Technology_Work_2.pdf.

Frey, C.B. and Osborne, M. (2013) The Future of Employment: How Susceptible Are Jobs to Computerisation? Working paper, Oxford University, Oxford, U.K.

Frey, C.B. and Osborne, M. (2017) The Future of Employment: How Susceptible Are Jobs to Computerisation? *Technology Forecasting and Social Change* 114: 254–280.

Gill, I., and Kharas, H. (2007) An East Asian Renaissance – Ideas for Economic Growth. Washington, DC: World Bank.

Glawe, L., and Wagner, H. (2016) The Middle-Income Trap: Definitions, Theories and Countries Concerned—A Literature Survey. *Comparative Economic Studies* 58(4): 507–538.

Glawe, L., and Wagner, H. (2017a) The People's Republic of China in the Middle-Income Trap? ADBI Working Paper No. 749. Tokyo: Asian Development Bank Institute (ADBI). An updated version of this paper is distributed as CEAMeS Discussion Paper No. 15. Hagen: Center for East Asia Macroeconomic Studies.

Glawe, L., and Wagner, H. (2017b) A Stylized Model of China's Growth Since 1978. SSRN Working Paper No. 2917433 and CEAMeS Discussion Paper No. 5. Hagen: Center for East Asia Macroeconomic Studies.

Grossman, G.M., and Helpman, E. (1991) Trade, knowledge spillovers, and growth. *European Economic Review* 35(2): 517–526.

Habakukk, H.J. (1962) *American and British Technology in the Nineteenth Century*. London: Cambridge University Press.

Kattan, R.B., Macdonald, K., and Patrinos, H.A. (2018) Automation and Labor Market Outcome – The Pivotal Role of High-Quality Education. Policy Research Working Paper 8474. Washington, DC: The World Bank.

ILO (International Labour Organization) Laborstat (database). Various years. Geneva: ILO, http:// laborsta.ilo.org/.

ITU (International Telecommunication Union) (2017) Measuring the Information Society Report 2017. Volume 1. Geneva: ITU. Data online available at: http://www.itu.int/net4/ITU-D/idi/2017/.

Islam, S.N. (2015) Will Inequality Lead China to the Middle Income Trap? DESA Working paper No. 142, New York: United Nations, Department of Economic and Social Affairs.

Kharas, H., and Kohli, H. (2011) What is the middle income trap, why do countries fall into it, and how can it be avoided? *Global Journal of Emerging Market Economies* 3(3): 281–289.

Keller, W. (2010) International Trade, Foreign Direct Investment, and Technology Spillovers, Chapter 19 in B. Hall, N. Rosenberg (eds.), Handbook of the Economics of Innovation, Elsevier North-Holland.

Leontief, W. (1952) Machines and Man. *Scientific American* 187(3): 150-164.

Levy, F., and Murnane, R.J. (2007) How Computerized Work and Globalization Shape Human Skill Demands. In: Suarez-Orozco, M. (ed.), Learning in the Global Era: International Perspectives on Globalization and Education. Berkeley, CA: University of California Press (pp. 158–174).

Lewis, W.A. (1954) Economic development with unlimited supplies of labor. *Manchester School of Economic and Social Studies* 22: 139–191.

Lewis, C. (2014) Robots Are Starting to Make Offshoring Less Attractive. *Harvard Business Review*. Online available at: https://hbr.org/2014/05/robots-are-starting-to-make-offshoring-less-attractive.

McKinsey (2017) A Future That Works: Automation, Employment, and Productivity. McKinsey Global Institute.

OECD (2005) *Learning a Living: First Results of the Adult Literacy and Life Skills Survey*. Paris: OECD.

Rodrik, D. (2016) Premature Deindustrialization. *Journal of Economic Growth* 21(1): 1-33.

Schireson, M., and Nguyen-Huu, D. (2017) Blue-Collar Revenge: The Rise Of AI Will Create A New Professional Class. Forbes, 6 April 2017. Online available at: https://www.forbes.com/sites/valleyvoices/2017/04/06/blue-collar-revenge-and-the-rise-of-ai/#338e613524c9.

Schwab, K. (2017) *The Fourth Industrial Revolution*. London: Penguin.

Vermeulen, B., Kesselhut, J., Pyka, A., and Saviotti, P.P. (2018) The Impact of Automation on Employment: Just the Usual Structural Change? *Sustainability* 10(5): 1661, https://doi.org/10.3390/su10051661.

Vivarelli, M. (2014) Innovation, Employment and Skills in Advanced and Developing Countries: A Survey of Economic Literature. *Journal of Economic Issues* 48 (1): 123–54.

Wagner, H. (2015) Structural Change and Mid-Income Trap – Under Which Conditions can China Succeed in Moving Towards Higher Income Status? *The European Journal of Comparative Economics* 12(2): 165–88.

World Bank (2012) Putting Higher Education to Work: Skills and Research for Growth in East Asia. World Bank East Asia and Pacific Regional Report. Washington, DC: World Bank.

World Bank (2016) World Development Report 2016: Digital Dividends. Washington, DC: World Bank.

World Economic Forum (2016) *The Future of Jobs – Employment, Skills and Workforce Strategy for the Fourth Industrial Revolution*. Geneva: World Economic Forum.