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

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Abstract: 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") and discuss the implications for developing Asia. In particular, we analyze the impacts of automation, artificial intelligence, and digitalization on the growth drivers of emerging market economies and the MIT mechanism. 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.

Keywords: automation; human capital; middle-income trap; developing Asia; economic growth and development; employment

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

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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 and1970s, which was soon followed by the so-called four “Asian Tigers” and subsequently by various ASEAN countries (especially Malaysia and Thailand). 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), the latter aspect especially applies to the ‘late developers’ such as China. 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). 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 successfully accomplish the change in the growth strategy are human capital accumulation, export sophistication, and TFP (see Glawe and Wagner, 2019). A recent development appears to put additional pressure 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 4th Industrial Revolution (World Bank, 2016; 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 4th Industrial Revolution will have strong negative implications on the export-manufacturing growth strategy.

We argue that the 4th 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 analyze the impacts of automation and AI on the growth drivers of MICs and the MIT mechanism. Moreover, we elaborate on 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 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 impacts of the 4th Industrial Revolution and the MIT concept. In Section 3, we then discuss how automation will affect the mechanisms of the MIT. Against this background, Section 4 analyzes the situation in developing Asia with a special focus on human capital and ICT skills. Section 5 concludes.

2. Related literature

The following two sub-sections are devoted to a brief discussion of the related literature strands, namely the literature on the impacts of automation and on the MIT concept.[1]

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 (Autor, 2015). While the academic literature related to the developments of this so-called "4th Industrial Revolution" is still relatively new, the fear that technological change has negative impacts on employment has a long history dating back to the Luddites in the early 19th century. However, so far, all the fears that technological progress and automation would create an unemployment crisis have proven groundless: In fact, automation has in general raised productivity and lowered unemployment since the job creation effect far offset the labor-saving effect of automation (cf. e.g. Vivarelli 2014). The main question that arises is: Will the 4th Industrial Revolution be different? 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 (World Economic Forum, 2016). Moreover, there is consensus among researchers that the 4th Industrial Revolution will have huge economic and

[1] For extensive surveys on the MIT concept see e.g. Glawe and Wagner (2016; 2019). Literature reviews on the impact of automation, digitalization, and AI on growth and employment are provided, among others, by Autor (2015), Deutsche Bundesbank Research (2018), and Vermeulen et al. (2018).

social-politic consequences. 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[2]: 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, among others the *productivity*, the *capital accumulation*, and the *deepening of automation effect* (cf. Acemolgu and Restrepo 2018). However, only the *reinstatement effect*, i.e., the creation of new tasks in areas where humans have a comparative advantage, will be able to compensate the displacement effect (Acemolgu and Restrepo 2018). Another interesting question is which jobs will be affected most by automation. Acemoglu and Autor (2011) distinguish between four occupations based on the skill requirements. In particular they distinguish between occupations that require *routine tasks* that are either i**)** *cognitive* (e.g. bookkeepers) or **ii)** *manual* skill intensive (e.g. cashiers) and those that require *non-routine tasks*, again being either **iii)** *cognitive* (e.g. teachers) or **iv)** *manual* skill intensive (e.g. hairdressers).[3] While the jobs of workers in occupations i) and ii) can be easily automated, the workers of occupation iii) can profit greatly from automation since their jobs are likely to be complemented by technological advances. Workers in occupation iv) are not directly affected by automation. Overall, automation leads to a shrinking share of middle-skilled and rising shares of high- and low-skilled employment and thus to a "hollowing out" of the labor market, accompanied by a fiercer competition and wage stagnation for middle and low skilled job as well as greater income inequality (Vermeulen et al. 2018).

2.2 Middle-income trap literature

Over the last decade, the term 'middle-income trap' 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 former are based on absolute middle-income thresholds and interpret the MIT as a prolonged growth slowdown at the MIR (see e.g. Eichengreen et al. 2012), whereas the latter refer to the per capita income relative to the US and usually interpret the MIT as a failed catching-up process (see e.g. Woo 2012). From a geographical standpoint,

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

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 whether China is also a potential MIT candidate (Glawe and Wagner 2019; Cai 2012). According to the meta-analysis of Glawe and Wagner (2019), the main empirical triggering factors identified by the empirical studies are the export structure, TFP, 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 Section 3.1, we first examine the impacts of an accelerated automation on the growth drivers of developing countries and emerging market economies (EMEs). In 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 to an innovation-productivity based growth model and discuss the increasing challenges due to automation.

3.1 Impacts of automation on the growth drivers of EMEs

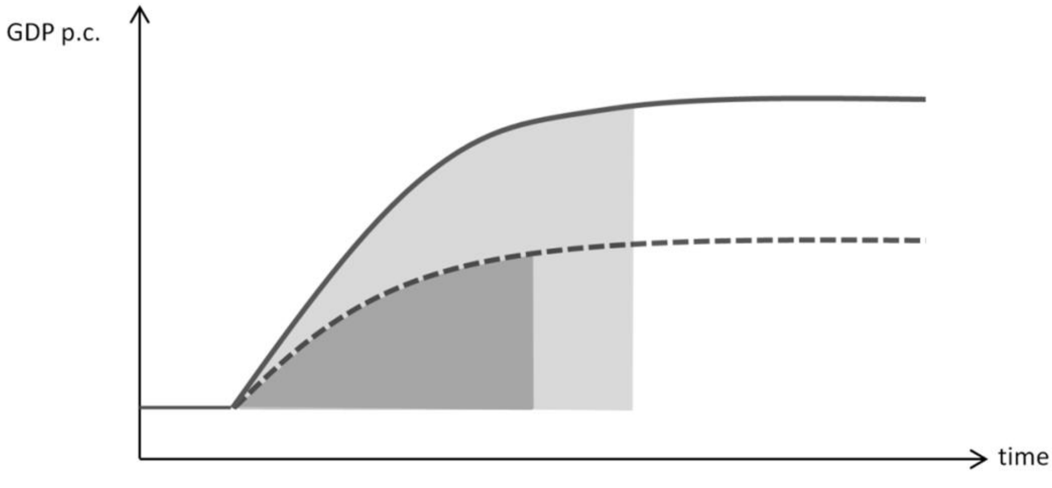
Structural change and trade/imitation are the two main growth drivers of developing countries. If these initial growth drivers become exhausted and there is no timely shift to an innovation based growth strategy, countries may become stuck in an MIT. Advances in AI and an accelerated automation will have important implications for these two growth engines 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 indicates that development countries are running out of industrialization opportunities sooner and at a lower level of per capita GDP than the early industrializers and thus, automation reinforces the “premature deindustrialization” trend identified by Rodrik (2016). A recent McKinsey (2017) study finds that although the manufacturing sector is already one of the most highly automated industries, there is still significant potential for further automation, amounting to 60 percent. Thus, in the future, automation will very likely even further reduce the employment and possibly even growth opportunities implied by structural change (dependent on the automation induced productivity growth effect). For current LICs and LMICs this means that shifting the labor force from the agricultural to the manufacturing sector will not create the same rapid growth as experienced by the Asian Tigers.

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 generate high transitory growth at an early development stage. However, as automation is becoming less costly, more and more advanced countries will reconsider offshoring labor-intensive jobs to developing countries because it could be more profitable to automate labor-intensive jobs and bring production home ("re-shoring") (Frey et al. 2016). That means, in the future, developing countries will also increasingly compete with advanced countries which will remain competitive locations. These developments will have negative impacts on the export opportunities of developing countries. In addition, EMEs 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), thus reinforcing the "premature deindustrialization" trend. 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. After focusing primarily on the dwindling export opportunities, we now discuss in more detail in how far automation affects imitation opportunities.

In the last decades, globalization induced great (economic) convergence advantages by enabling developing countries to generate knowledge transfers/spillovers via two main channels, namely a) via *trade,* in particular, the *import of high-end products* (Coe and Helpman 1995) and b) via *foreign direct investment (FDI)* (Keller 2010). Among the East Asian countries, Japan is a prominent example of the former, more ambitious strategy, which requires a well-developed infrastructure and experienced engineers to absorb the knowledge incorporated in imported high-end products (Wagner 2019), whereas China focused on attracting FDI. On-the-job-training enabled Chinese workers to first learn about the foreign technology and then to transfer the "blueprints" to domestic companies. That is, by being integrated into the global production chain and serving as a "work bench", China created the preconditions for successfully following an imitation-based growth strategy (and later even an innovation strategy). Due to China's huge and thus (for foreign investors) attractive domestic market, China was also able to force foreign companies into joint ventures to even better absorb technologies (Wagner 2019). It is questionable, however, if in the future, developing countries will have the same opportunities as today's MICs (and especially today's UMICs). As already explained above, due to the possibilities offered by automation, fewer companies of advanced economies will engage in trade with developing countries but prefer to locate production facilities closer to their home countries. Thus, it will become more difficult for developing countries to internalize technological/knowledge spillover effects that usually arise through FDI (see e.g. Coe and Helpman 1995). Thus, the reshoring trend significantly reduces the potential of imitation via the FDI channel, which has formerly contributed to the high growth of many MICs. Theoretically, developing countries could of course try to follow Japan's alternative strategy by using reverse engineering. While this could still work for some UMICs, especially the LMICs will most probably have severe problems to implement this ambitious strategy which has much higher human capital requirements.[4] In sum, today's LIC/LMICs will have to switch earlier to an innovation-based growth strategy, which requires a much higher level of human capital than an imitation strategy does. However, at this LI/LMI development stage, 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.

Figure 1. Initial growth push with and without accelerated automation



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

[4] In this context, Africa provides a good example: Due to the lack of skilled human resources, advanced technology "gifts" of developed countries have not been able to induce the desired effect of knowledge spillovers (and thus, also increased imitation opportunities/capabilities).

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- and imitation-driven 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 1.

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

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 and 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. The development of rising wages in this scenario 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 (robots) is relatively high). 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 adoption (World Bank, 2016, pp. 22-23). Taking this 'adoption time lag' into account, the share of employment that can be automated and computerized declines, however, it is still relatively high, e.g. 55 percent for China, 52 percent for Thailand, and 49 percent for Malaysia (World Bank 2016).

In Section 2.1 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

[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.

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). Option (b) does not require such advanced skills as Option (a) but would lead to a higher unproductive service sector share. Hence, aggregate productivity and growth will decline. Moreover, since productivity is a key factor for overcoming the MIT, this development would pose a hindrance (for the EMEs) of catching-up to the advanced countries and thus increase the probability of an MIT. The greater the degree of skill-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 to have Option (a) and thus, 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 unstable 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 is related to income disparities: Rising inequality due to the polarization of the labor market may result in a limited home market for technologically more advanced goods and thus, will make product development more difficult (unless the products can be easily exported) which, in turn, limits export sophistication, another important MIT triggering factor (Glawe and Wagner 2019). 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 Sections 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 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 for developing countries 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 2. Increased skill requirements due to automation

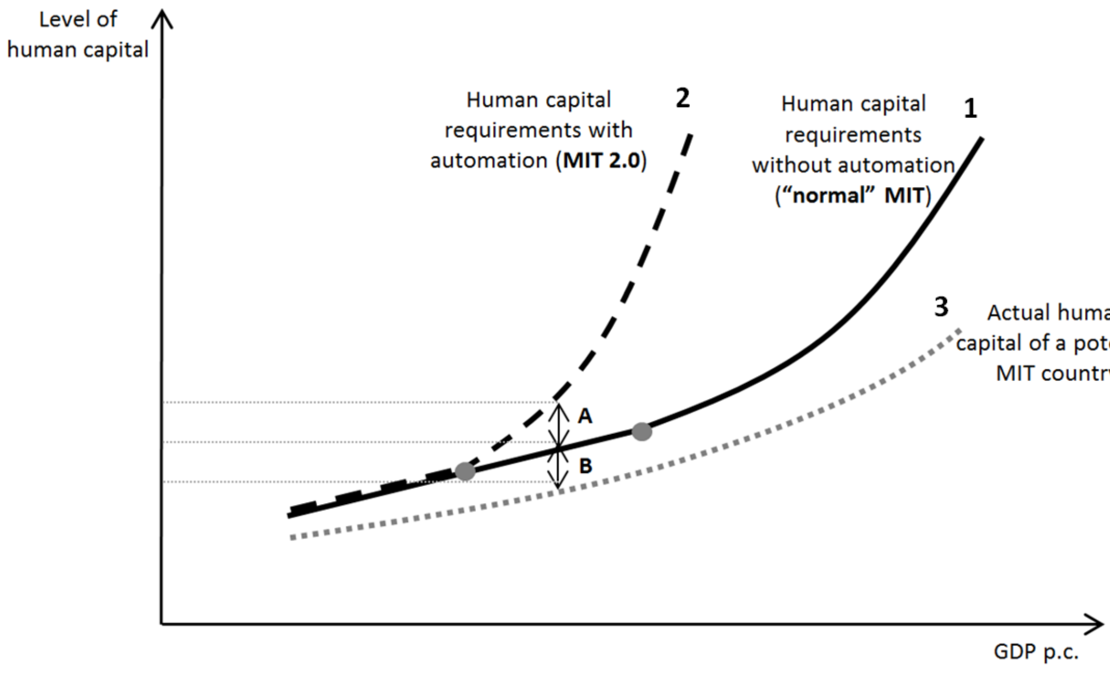


Figure 2 summarizes in how far the human capital/skill requirements to overcome an MIT change via automation: The thick lines labelled as human capital requirement curves represent this skill and human capital level (at different income stages) that is needed to successfully overcome the MIT. The black thick line (1) presents the requirement curve in the usual environment of MIT countries (without accelerated automation), whereas the thick black dashed line (2) presents the requirement curve for an environment characterized by accelerated automation (MIT 2.0). The grey dotted line (3) 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, 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.

Note that we draw here a rather pessimistic picture. Of course, the 4th Industrial Revolution also offers opportunities for developing countries. For instance, it could also be that automation leads to increasing returns of human capital (as postulated by endogenous growth models) and thus, enhances the rate of return to human capital. As a consequence, the road to high-income status could be even shortened. In that case, the thick dashed curve would not necessarily increase so steeply but turn concave after reaching a certain threshold. Finally, it is important to note that the human capital – economic development relationship is subject to the problem of reverse causality: While it is true that human capital can determine economic performance, high incomes and fast growth can also stimulate human capital by inducing investment in education. Thus, human capital and economic development are mutually reinforcing. However, as implied by our discussion, we think that automation will likely limit the growth opportunities of developing countries and thus, also limit the positive effect of higher incomes on human capital.

4. Implications for developing Asia

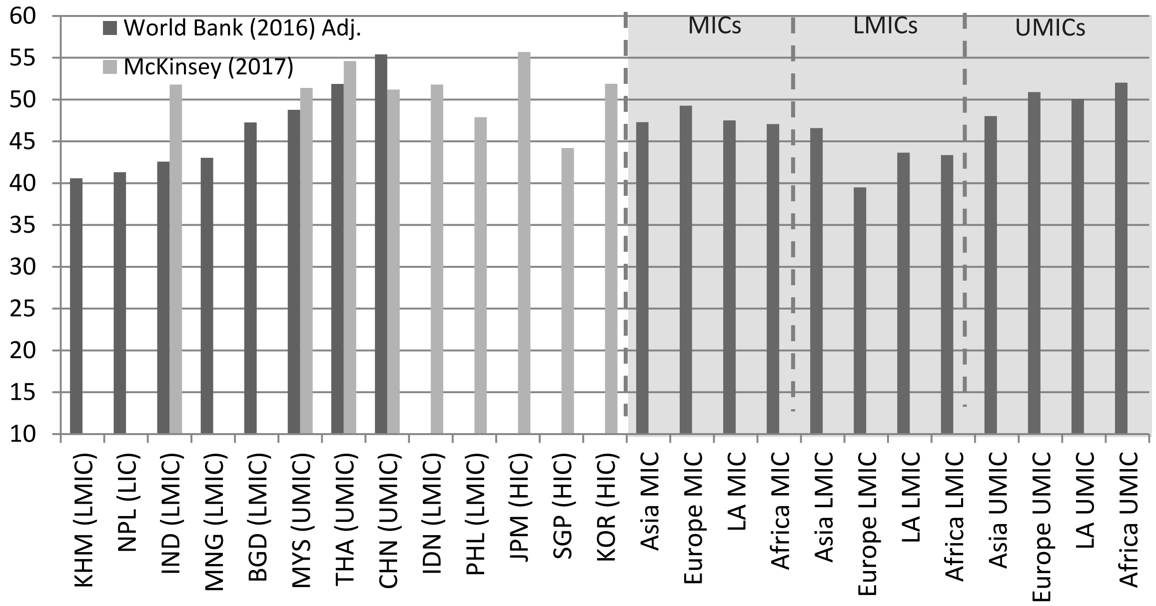
In Section 4 we analyze in how far the Asian countries are prepared to cope with the increasing challenges associated with the catching up process in an increasingly automated world/environment. We will focus particularly on East Asian, South East Asian, and South Asian countries.

Since our analysis in 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

[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

general educational situation (Section 4.1), (ii) the percentage of the workforce that works in occupations that require non-routine cognitive and interpersonal skills (Section 4.2), as well as (iii) an ICT development (IDI) index (Section 4.3). Finally, Section 4.4 briefly summarizes our main findings and elaborates on which Asian countries are most susceptible to falling into an MIT 2.0. 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, both displayed in Figure 3: the (adjusted) World Bank (2016) index (in dark grey) and the McKinsey (2017) index (in light grey).

Figure 3. Automation potential



Source: Data from World Bank (2016). *Note:* "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 2017 World Bank classification.

Overall, in all LICs and LMICs in our sample, the automation potential ranges between 40 and 50 percent. Bangladesh, Indonesia, Philippines, and India are the LMICs with the highest automation potential in the sample (with values of 47, 48, 52, and (mean) 47 percent, respectively). In international comparison, we can state that MICs in all regions (Asia, Africa, Europe, Latin America) face a relatively similar automation potential. However, at the

determine whether automation is beneficial or detrimental. Besides, the actual human capital - growth relationship might be more nuanced. For instance, there could be indirect effects via other channels as well as threshold effects. One important aspect in this context is the importance of institutional quality, in particular the question of whether human capital can only unfold its positive effects if the institutional setup is adequately designed.

more disaggregated level, strikingly, the Asian LMICs have the highest automation potential while the Asian UMICs have on average the lowest automation potential. 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.

4.1 General educational indicators

Section 4.1 provides an overview of the general educational situation in the Asian countries. In particular, we compare a widely used quantitative indicator, namely the expected mean school years (in 2017) with the learning-adjusted years of schooling (LAYS), which adjust the former measure by a qualitative component (the TIMSS test scores). Table 1 (p. 17 of this paper) summarizes our findings. All countries in our sample report mean school years above 8, in most cases even above 10. China, Mongolia, the Philippines, and (rather surprisingly) Sri Lanka report the highest values around or above 13 years. However, as soon as we adjust for the qualitative component, the picture changes dramatically and only Vietnam manages to break the 10 year threshold (jumping from rank 7 to rank 1 in our Asian MIC sample). While China and Mongolia can keep their top-3 positions, Sri Lanka loses almost 5 years compared to the regular mean school years. Also, Indonesia, Laos, Mongolia, the Philippines, and all South Asian LMICs record a four to five year difference, whereas Cambodia and Malaysia only lose 2 to 3 years (rising in the rankings). The East Asian HICs and the US lose only one and two years, respectively. Overall, China, Vietnam, Malaysia, and Mongolia manage to reach similar LAYS than the East Asian HICs and the US. Probably most surprisingly is the sharp drop of India from 10 to below 6 years. Overall, it is important to note that traditional (quantitative) human capital measures may not adequately depict the actual educational situation in a country and might give the impression that a country is well prepared to cope with increasing skill requirements while this is in fact not the case.[7]

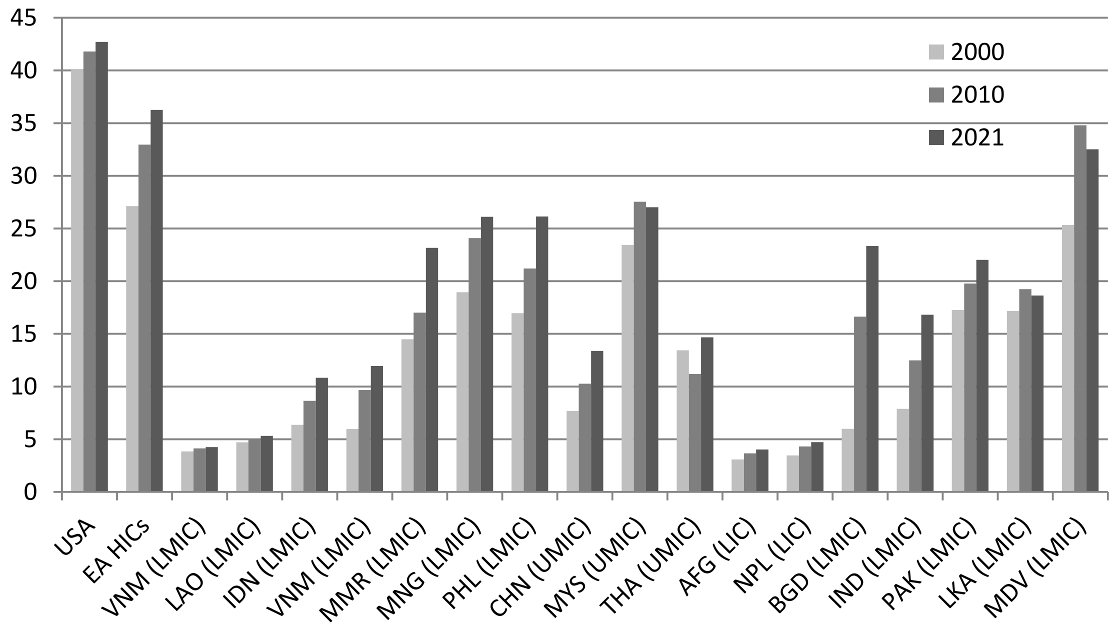
4.2 Percentage of the workforce that works in occupations that require high skills

Section 4.2 focuses on the development of the skill level of workers in the Asian countries by using occupational data. 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-, middle-, and low-skilled) classified according to major groups

[7] This is even more so if international databases use data that is provided by the countries themselves and which could be manipulated.

as defined in one or more versions of the ISCO. High-skilled occupations require non-routine cognitive and interpersonal skills (see also World Bank, 2016) which are usually not substituted but complemented by automation and technological advances, that is technology is labor-augmenting and has primarily positive effects on the overall economy (see also Sections 2.1 and 3.2). In general, East Asian, South Asian, and Latin American MICs all have relatively similar shares of people working in high-skilled occupations, ranging from 15 to 19 percent. At the country level perspective, Figure 4 shows 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. Myanmar, Mongolia and the Philippines record the highest values. Strikingly, many East Asian LMICs outperform the East Asian UMICs, particularly China and Thailand. 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. Among the LMICs, Bangladesh and Pakistan record the highest values, but also India has seen strong increases over the last decade. Sri Lanka's performance has on average seen declining shares of workers in high-skilled occupations since 2005 which is a bit worrying.

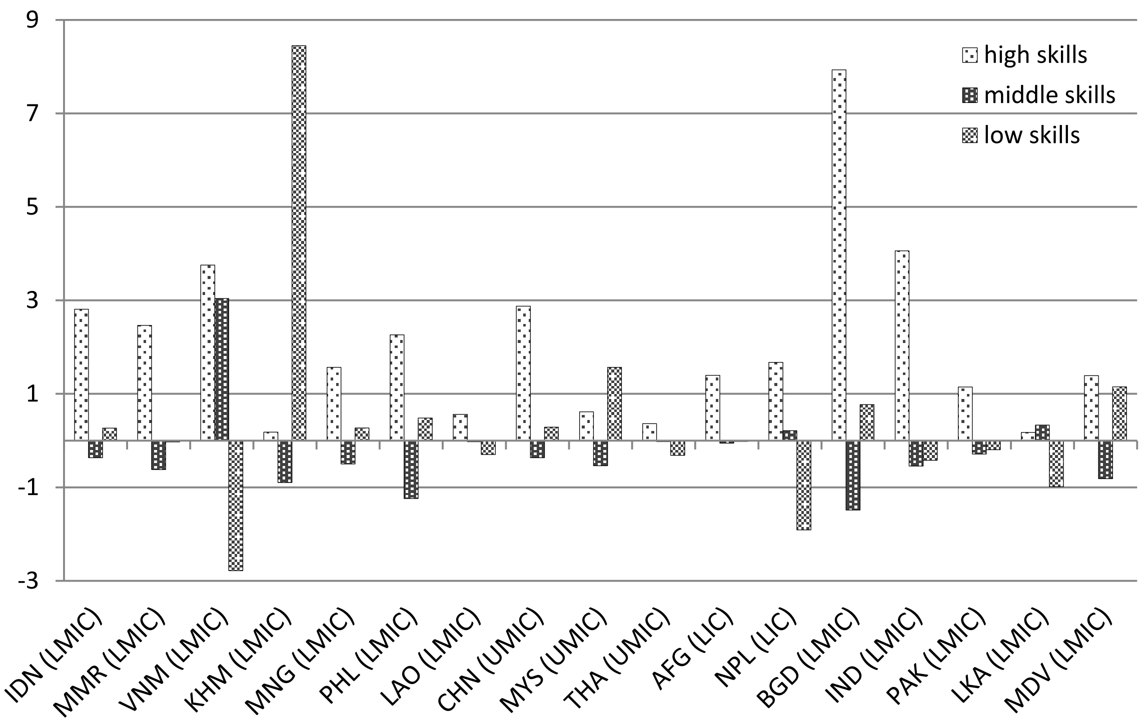
Figure 4. Percent of the population working in high-skilled occupations – East Asia (LMICs)



Source: Data from ILO Laborstat. *Note:* See Figure 3 notes.

The combination of a higher high-skilled and 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. Figure 5 shows the total change in employment shares between 2000 and 2017. In sum, 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, except for Cambodia, we cannot state a strong increasing trend in the employment share in low-skilled occupations, which is in general a positive sign. Among all Asian LMICs, the performance of Vietnam, Bangladesh and India appears to be particularly promising regarding the ratio of the different skill-level occupational shares (compared to the other countries).

Figure 5. Total change in employment shares (in 100%) – East Asia (2000-17)

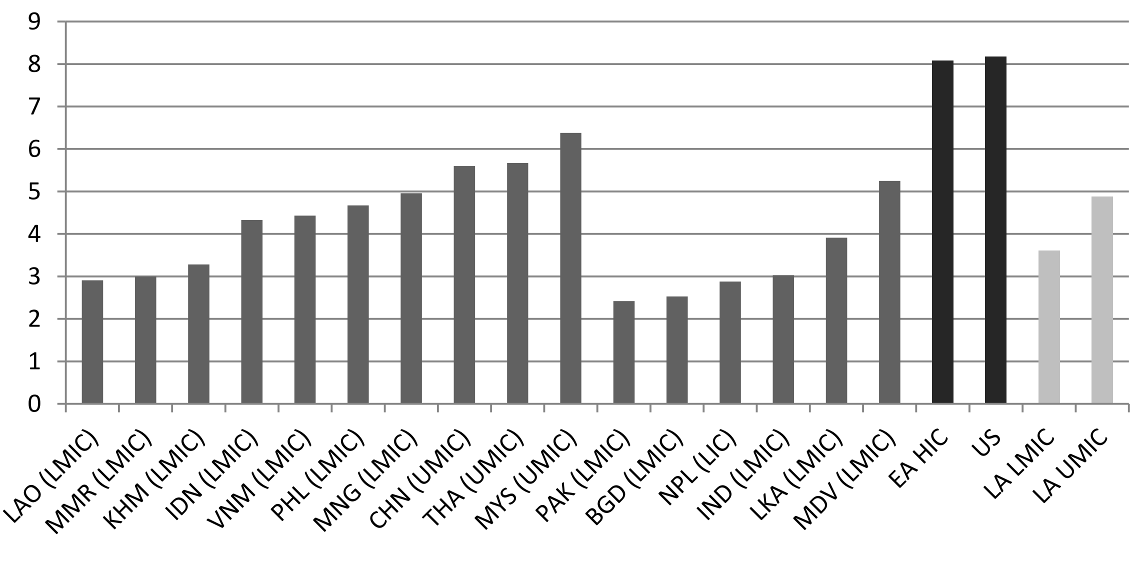


Source: ILO Laborstat. *Note:* See Figure 3 notes.

4.3 ICT Development Index (IDI)

The ICT Development Index IDI is a composite index that consists of three sub-indexes (ICT access, use, and skills) and due to the ITU (2017). In 2017, the worldwide mean IDI amounts to 5.11; the minimum and maximum values are 0.96 and 8.98, respectively. Figure 6 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 percent 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 percent 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 percent higher, respectively). 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 percent higher score. 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.

Figure 6. IDI – East Asia (MICs)



Source: ITU (2017). *Note:* See Figure 3 notes.

4.4 Summary of our main findings

Table 1 provides a summary of our key findings. Regarding the LAYS measure, we construct an overall score based on a) the number of the LAYS and b) the difference between the LAYS and the unadjusted mean school years. “+++” indicates a very good performance (relatively high LAYS close to the Asian frontiers, small difference to the unadjusted school years), “++” a positive performance (high LAYS and medium difference or medium LAYS and small difference), “+” indicates a regular performance (medium LAYS and medium difference), “-“ indicates a relatively poor performance (medium LAYS and high difference or low LAYS and medium difference), and “--" implies a poor performance (low LAYS, high difference).[8] For the last two columns, a “-“, “+”, “++”, and “+++” correspond to an employment share in high-skilled occupations below 5 percent, between 5 and 15 percent, between 15 and 25 percent, and above 25 percent, 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. Among the (South) East Asian LMICs, Malaysia performs best, reaching top scores in every category and showing in general a strong catching up tendency to the East Asian HICs and the US. Therefore, from the human capital and skill requirement standpoint, it has the lowest probability to experience an “MIT 2.0”. Also, Vietnam, Mongolia, the Maldives, and China show an overall good performance regarding the human capital and skill indicators. The performance of Laos and Nepal is most worrying since they record low values in all categories. Among the South Asian LMICs, Bangladesh is the best performing country; however, it has still relatively low general educational levels with learning-adjusted years of schooling around 6.5. The two LICs Nepal and Afghanistan and – somewhat surprisingly – India bring up the rear. Interestingly, South Asian LMICs perform significantly lower than the East Asian LMICs regarding the LAYS and the IDI.

[8] High, medium, and low LAYS correspond to above 9 LAYS, between 6.5 and 9 LAYS, and below 6.5 LAYS. A high, medium, and small difference between the LAYS and the unadjusted school years correspond to a difference above 4 years, between 3 and 4 years, and below (and in one borderline case around) 3 years.

Table 1. Summary – Human capital indicators in Asian LICs

Country	**Income Class**	**Region**	**Years**	**LAYS**	**Diff**	**LAYS Score**	**High Skills**	**IDI17**
Cambodia	LMIC	South East Asia	9.6 (14)	6.9 (9)	-2.7	++	-	-
Indonesia	LMIC	South East Asia	12.3 (6)	7.9 (8)	-4.4	-	+	+
Laos	LMIC	South East Asia	10.8 (11)	6.4 (13)	-4.5	-	-	-
Mongolia	LMIC	East Asia	13.6 (1)	9.5 (3)	-4.1	+	+++	+
Myanmar	LMIC	South East Asia	9.9 (13)	6.7 (11)	-3.2	+	++	-
Philippines	LMIC	South East Asia	12.8 (4)	8.4 (6)	-4.4	-	+++	+
Vietnam	LMIC	South East Asia	12.3 (7)	10.2 (1)	-2.1	+++	+	+
China	UMIC	East Asia	13.3 (2)	9.7 (2)	-3.6	++	+	++
Malaysia	UMIC	South East Asia	12.2 (8)	9.1 (4)	-3.1	+++	+++	+++
Thailand	UMIC	South East Asia	12.4 (5)	8.6 (5)	-3.7	+	+	++
Afghanistan	LIC	South Asia	8.6 (16)	4.9 (15)	-3.7	-	-	NA
Nepal	LIC	South Asia	11.7 (9)	6.9 (10)	-4.8	-	-	-
Bangladesh	LMIC	South Asia	11.0 (10)	6.5 (12)	-4.5	-	++	-
India	LMIC	South Asia	10.2 (12)	5.8 (14)	-4.4	--	+	-
Pakistan	LMIC	South Asia	8.8 (15)	4.8 (16)	-4.1	--	++	-
Sri Lanka	LMIC	South Asia	13.0 (3)	8.3 (7)	-4.7	-	+	-
Maldives	UMIC	South Asia	NA (NA)	NA (NA)	NA	NA	+++	++
US	HIC	North America	13.3	11.1	-2.2			
EA HIC	HIC	East Asia	13.6	12.2	-1.3			

Note: "LIC", "MIC", "LMIC", "UMIC", "HIC" stand for low-, middle-, lower-middle, and upper-middle, and high-income country. "LAYS" denotes the learning-adjusted years of schooling, "High Skills" denotes the employment share in high-skilled occupations and "IDI17" stands for the ICT Development Index for the year 2017. The LAYS ranks (of our Asian MIC sample) are in brackets.

5. Conclusion

In our paper, we have analyzed how the current and future challenges of automation and the 4^{th} 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". 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, 2019, 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 4th 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 human capital performance. In particular, we focused on the percentage of the (learning-adjusted) mean school years, 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 the LAYS measure. Among the East Asian LMICs, Malaysia's performance is outstanding, but also Vietnam, China, and Mongolia score well. Among the South Asian LMICs, Bangladesh and Pakistan are the best-performing countries. Please note that our analysis only gives a first impression of the situation in developing Asia and ability 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 (2019), Section 4.5. Future research should focus more strongly on the interconnections between human capital, institutional quality, and automation/artificial intelligence.

References

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

Acemoglu, Daron, and Pascual Restrepo. 2018. Artificial Intelligence, Automation and Work. NBER Working Paper 24196.

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

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

Cai, Fang. 2012. The Coming Demographic Impact on China's Growth: The Age Factor in the Middle-Income Trap. *Asian Economic Papers* 11(1): 95-111.

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

DBR. 2018. Digital Economics - How AI and Robotics Are Changing Our Work and Our Lives. EU Monitor Digital Economy and Structural Change. Deutsche Bundesbank.

Eichengreen, Barry, Donghyun Park, and Kwanho Shin. 2012. When Fast-Growing Economies Slow Down: International Evidence and Implications for China. *Asian Economic Papers* 11(1): 42-87.

Frey, Carl Benedikt et al. 2016. *Technology at Work v2.0 – The Future Is Not What It Used to Be*. Citi GPS: Global perspectives & solutions.

Glawe, Linda, and Helmut Wagner. 2016. The Middle-Income Trap: Definitions, Theories and Countries Concerned - A Literature Survey. *Comparative Economic Studies* 58(4): 507-38.

Glawe, Linda, and Helmut Wagner. 2019. China in the Middle-Income Trap? forthcoming in: *China Economic Review*.

ILO (International Labour Organization) Laborstat (database). Various years. Geneva: ILO.

ITU (International Telecommunication Union). 2017. Measuring the Information Society Report 2017. Volume 1. Geneva: ITU.

Keller, Wolfgang. 2010. International Trade, Foreign Direct Investment, and Technology Spillovers, B. Hall, N. Rosenberg (eds.), Handbook of the Economics of Innovation, Elsevier.

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

McKinsey. 2017. A Future That Works: Automation, Employment, and Productivity.

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

Vermeulen, Ben, Jan Kesselhut, Andreas Pyka, and Pier Paolo Saviotti. 2018. The Impact of Automation on Employment: Just the Usual Structural Change? *Sustainability* 10(5).

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

Wagner, Helmut. 2019. On the (Non-) Sustainability of China's Development Strategies. *Chinese Economy* 52(1): 1-23.

Woo, Wing Thye. 2012. China Meets the Middle-Income Trap: The Large Potholes in the Road to Catching-Up. *Journal of Chinese Economic and Business Studies* 10(4): 313-36.

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. 2016. World Development Report 2016: Digital Dividends. Washington, DC.

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