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# The Future of Work(ers) in the Age of Technological Revolution

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# The Future of Work(ers) in the Age of Technological Revolution †

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## Abstract

This chapter reviews key literature on the determinants and implications of technological change associated with the Third and Fourth Industrial Revolutions, which have spread globally since the late 20th century, and presents descriptive evidence. The main conclusion is that while technological progress has not significantly threatened overall employment opportunities, it has clearly contributed to rising income inequality. Consequently, a future devoid of employment is not anticipated, although the prospects for equality remain uncertain. I argue that to maximize the benefits of technological advancement, education must evolve in tandem with technology, equipping individuals to work alongside new innovations throughout their lives. This would enable workers to fully leverage *automation* of routine tasks and *augmentation* of abstract and cognitive tasks, fostering teamwork, problem-solving, flexibility, creativity, and social intelligence. Furthermore, productivity growth driven by technological progress is likely to increase demand for both traditional and new goods and services, generate income gains that increase demand for quality, accelerate structural change, and exert pressure on resource utilization.

**Keywords:** Technological Revolution, Jobs, New Tasks, Education, Income Distribution, Resource Utilization.

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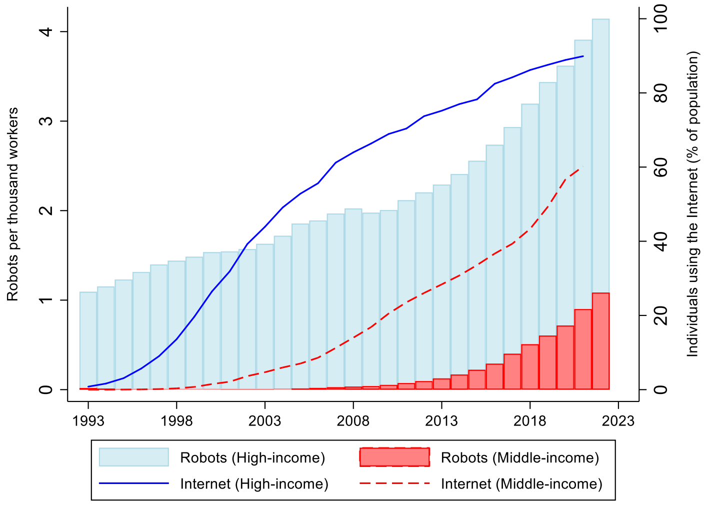
# 1. Introduction

The Third and Fourth Industrial Revolutions offer vast opportunities for economic progress, while simultaneously posing significant challenges to the world of work. This phase is marked by emerging technological advances in a large number of fields, including information and communication technologies, the internet, biotechnology, renewable energy, robotics, artificial intelligence, nanotechnology, quantum computing, the internet of things, big data, and 3D printing, among others. Achieving shared prosperity will hinge on workers' ability to adapt to the evolving demands of the labor market and the equitable distribution of productivity gains from new technologies.

Some of these technologies, especially industrial robots, significantly expand production scale, resulting in price reductions, increased consumption, and greater demand for inputs and non-renewable raw materials. This calls for a reevaluation of resource management and environmental protection practices, particularly in weaker regulatory contexts like low- and middle-income countries, and in the face of severe climate change.

Figure 1 illustrates the recent evolution of two key technologies from the Third and Fourth Industrial Revolutions: (i) the internet and (ii) industrial robots, in high-income and middle-income countries from 1993 to 2022. In high-income countries, internet use expanded rapidly since 1993, reaching 61.2% of the population by 2007 and 90% by 2021. In middle-income countries, internet adoption accelerated after 2000, growing steadily to 26.1% in 2012 and 60.2% by 2021. Meanwhile, robot adoption in high-income countries increased steadily throughout the period, accelerating in the 2010s from 1.1 robots per thousand workers in 1993 to 4.1 by 2022. In contrast, robot adoption in middle-income countries remained near zero until 2010, reaching 1.1 robots per thousand workers by 2022, still far below high-income countries. These trends highlight a lag in technology adoption in developing countries, though they are rapidly catching up globally.

Figure 1: Global adoption of internet and robots




*Notes.* Stock of robots per thousand workers calculated for all countries included in the International Federation of Robotics (IFR) dataset (45 high-income countries and 29 middle-income countries). Country's employment is fixed in 1995. Individuals using the internet obtained from the World Developing Indicators (ICT Database) from The World Bank, including all countries worldwide.

Technological change profoundly impacts the economic and social structures of communities. It generates enormous opportunities to improve quality of life while posing significant challenges, especially for governments, to ensure a smooth transition that allows all members of society to benefit from technological progress. One key message of this chapter is that education must evolve alongside technology, echoing Tinbergen's ideas. Individuals should be prepared to work with new technologies throughout their lives. This involves taking full advantage of: (i) the *automation* of routine, repetitive, manual, and time-consuming tasks; and (ii) the *augmentation* of abstract and cognitive tasks, driven by AI, for instance, across all economic sectors. People should focus on new tasks and jobs that leverage human innate advantages such as teamwork, problem-solving, flexibility, creativity, and social intelligence. Examples include R&D, process and product design, and improving organizational practices, distribution channels, and customer services.

Productivity growth from technological progress will increase demand for both traditional and new goods and services, leading to income gains and a higher *demand for quality,* as broadly defined. This will deepen *structural change*, with a growing fraction of workers providing services to society. In this context, it is desirable for communities to allocate more resources to investments in science and education. This will level the playing field and form highly educated global citizens capable of fully benefiting from technological progress while being aware of their carbon footprint for future generations.

This chapter is organized as follows. Section 2 provides a brief contextual discussion on the historical background of the Agrarian and the First and Second Industrial Revolutions, along with recent changes brought by the Technological Revolutions. Section 3 offers a non-exhaustive review of specialized literature in Economics, focusing on Labor, Growth, Development, and Trade, and examines the relationship between technological change and socioeconomic outcomes. Section 4 presents basic facts about the main determinants and likely consequences of industrial automation. Section 5 concludes.

## 2. Contextualization

### 2.1 Historical perspective

The origins of material accumulation, economic growth, and inequality date back to the Agricultural Revolution, approximately 10,000 years ago. During this period, humans transitioned from a nomadic lifestyle to a sedentary one, shifting from hunter-gatherers to producers. The ability to settle in fixed locations and accumulate grain and domesticated animals led to the formation of towns and eventually cities. These surpluses facilitated the emergence of religious, military, and administrative activities. Private property and the State, two fundamental institutions of the modern world, also have their roots in this era ([1]).

A fascinating study of 186 primitive communities, known as the standard cross-cultural sample, found that four out of five hunter-gatherer communities had no obvious leaders, while three-quarters of agricultural societies were organized around power relations, hierarchies, and material inequalities ([2]). The development of agricultural economies led to increasingly complex hierarchical structures, evolving into hereditary domains, kingdoms, and empires. These entities developed various strategies to concentrate power and wealth, including pillage, wars, taxes, and tributes. In pre-modern societies, fortunes were primarily based on political power, coercion, and domination rather than economic activities.

Advancements in agriculture, currency, and trade multiplied material gains, increased the wealth of the nobility, and facilitated the rise of the middle classes—the *bourgeoisie*—who progressively gained economic power and political participation.

The First and Second Industrial Revolutions, commencing approximately 250 and 150 years ago respectively, introduced transformative technologies such as the steam engine, spinning machine, trains, and light bulbs. These innovations exponentially increased production and productivity, leading to significant socioeconomic changes, including large-scale migrations from rural to urban areas and transformations in transportation, communication, industry, and commerce. These changes were characterized by new forms of production, work, and organizational structures.

Deaton ([3]) identifies this period as the origin of inequality between nations, as the Revolutions dictated the pace of material progress and created disparities between advanced and lagging economies. Initially, the new production methods generated substantial profits for the bourgeoisie, who owned and controlled capital, without benefiting the broader population. The masses transitioned from rural deprivation to exploitation in large factories, living in poor conditions in industrial city suburbs. This environment fostered the emergence of union, anarchist, and socialist movements in mid-19th century England.

Over time, material progress extended to much of society. Countries such as Germany, France, much of Western Europe, North America, and later Japan, which joined this combined process of technological transformation and modern capitalism, experienced a sustained increase in the standard of living for the average citizen over approximately two centuries. Today, this standard of living remains significantly higher than that of the average inhabitant of the developing world. The economic advantages gained by developed nations during this period enabled them to dominate and, in some cases, exploit much of the rest of the world.

## 2.2 Recent changes

The Third and Fourth Industrial Revolutions, also known as the Digital and Industry 4.0 Revolutions, respectively, began at the end of the 20th century and continue into the 21st century. These revolutions primarily originated in the United States and Japan and are closely associated with advancements in information and communication technologies (ICTs), including the widespread use of computers, digital technologies, and the Internet. Additionally, they encompass significant progress in biotechnology, such as the manipulation of living cells for medical and nutritional purposes, and the adoption of renewable energy sources aimed at reducing dependence on fossil fuels and mitigating their substantial ecological impacts.

The Fourth Industrial Revolution is particularly characterized by the increasing significance of emerging technologies such as robotics, nanotechnology, quantum computing, 3D printing, and artificial intelligence, among other nascent technologies.

The adoption of ICTs has fostered globalization and facilitated the expansion of large multinational companies. The widespread use of computers, cell phones, and the Internet has promoted global connectivity and democratized access to knowledge. In this new context, while some jobs have disappeared, particularly those associated with automated routine tasks, many others have been created. These new jobs span professional occupations, low-skilled services, e-commerce, and digital working platforms.

Many scholars argue that control over the flow of information can sometimes favors disinformation, thereby enhancing the activities of radicalized groups. Others suggest that access to new technologies remains unequal, particularly in the least developed countries and among the lowest social strata.

## 3. Specialized literature in economics

Technological progress is often considered as the main determinant of economic progress and, simultaneously, a leading explanation for rising inequality. Early literature on skilled-biased technological change posits that technology complements skilled labor, therefore increasing the relative demand for and wages of skilled workers ([4] [5] [6]). Recent theories argue that the complementarity or substitutability between technology and labor occurs not at the worker skill level, but rather at the *task* level ([7] [8]). This framework assumes that computers and automation technologies are more likely to substitute routine tasks performed by workers in the middle of the skill distribution, complement analytical and interactive tasks typically undertaken by skilled workers, and have no predictable impact on routine manual tasks commonly carried out by unskilled workers. These assumptions underpin the *polarization hypothesis*, which has effectively explained the evolving labor market pattern in developed countries since the 1980s, characterized by employment and wage gains at both ends of the skill distribution, primarily in service occupations, at the expense of middle-skill workers predominantly employed in manual, production, and clerical jobs ([7] [9] [10] [11] [12] [13]).

The story seems to have been different in the developing world, where evidence supporting the polarization hypothesis is either limited or absent ([14] [15] [16] [17]). Developing countries lag behind high-income countries in various dimensions, with the most evident being income per capita, investment, education, health, infrastructure, and institutional quality. The adoption of new technologies is no exception. For instance, PIAAC data indicates that, on average, 35 percent of workers in Latin America report using a computer at work, compared to 62 percent in OECD member countries ([18]). In terms of typical automation technology, such as industrial robots, Figure 1 illustrates that robot adoption in middle-income countries only began to rise in the 2010s. By 2022, it reached approximately 1 robot per thousand workers, significantly lower than the 4 robots per thousand workers in high-income countries. These statistics suggest that developing countries are still in the early stages of technology adoption, which may be a key factor explaining the absence of labor market polarization.

Many high-income countries, along with some developing economies, have also seen a narrowing gap between men and women in labor force participation, paid work hours, education, and earnings ([19] [20]). In developed economies, the gender wage gap has been visibly narrowing since at least the 1970s. The leading explanations emphasize supply-side factors, such as improvements in education and work experience that benefited women relative to men, and the larger negative impact of de-unionization on male wages compared to female wages ([21] [22] [23]). On the demand side, rising globalization and automation since the 1980s have driven a sharp decline in manufacturing employment and a shift towards sectors that are more education- and women-intensive, such as professional and personal services ([24] [4] [25]).

Several authors argue that computer adoption has changed the nature and conditions of work in ways that benefit women more than men. Weinberg ([26]) finds that computer adoption explains over half of the increased demand for female labor. Bacolod and Blum ([27]) attribute 20% of the narrowing gender wage gap to the rising value of cognitive and personal skills, which are more prevalent among women. Similarly, Borghans et al. ([28]) argue that technological and organizational changes increased the importance of interactive and interpersonal skills, improving outcomes for under-represented groups, including women. In the task-based framework of Autor et al. ([7]), computers substitute for routine tasks, so groups with higher routine task intensity initially experience faster adoption and a stronger shift towards non-routine tasks. Spitz-Oener ([9]) supports this hypothesis, noting that a declining price of computers lowers rewards for routine tasks, while complementing non-routine analytical and interactive tasks, increasing productivity. Black and Spitz-Oener ([29]) find that task changes explain half of the decline in the gender wage gap in West Germany between 1979 and 1999. They document that women experienced a larger shift from routine to non-routine tasks, especially in jobs more exposed to workplace computerization.

Recent theories extend the task-based model to predict the effects of industrial automation on employment and wages (e.g., [30] [31]). Robots displace low-skilled workers by taking over manual routine tasks, reducing labor demand and wages (*substitution* effect). Simultaneously, robots reduce production costs and increase total factor productivity, increasing labor demand and wages (*reinstatement* effect). These opposing forces depend on labor mobility and how the gains from automation are distributed ([32]). Additionally, cross-industry input-output effects (via buyer-seller linkages) and between-industry shifts also play a role ([33]). There might be aggregate demand effects through changes in wages, relative prices, and shifts in consumption patterns. Indirect effects may also arise from changes in competition and market structure ([34]).

Evidence suggests that robots have replaced and reduced wages of low-skilled workers engaged in routine manual tasks ([35] [36] [37] [38] [39]). At the same time, robot adoption boosts value-added per worker and total factor productivity, lowers output prices, improves product quality, increases demand for skilled labor, and expands production, exports, and imports of intermediate inputs ([40] [41] [42] [43] [44] [45]). In the U.S. and Germany, displacement effects in manufacturing were offset by new jobs in services ([46] [47]). In Germany, automation has been linked to more stable employment for incumbents and to higher quality new jobs, while younger cohorts have shifted from vocational training toward higher education.

Recent research shows that robot adoption is concentrated in the largest and most productive firms, which grow further and may gain market share at the expense of competitors, both domestically and internationally ([34] [48] [49]). Studies using firm-level data from France (([48] [49] [50]), Spain ([51]), Denmark ([38]), Indonesia ([52]), and the U.S. ([53] [54]) show that robot adopters are typically large manufacturing firms highly involved in international trade. Furthermore, robots and exporting can be complementary to improve productivity ([51]). Since these firms tend to have lower labor shares than the average firm, automation can lead to a sustained decline in labor's share of value added, increasing the concentration of economic activity among “superstar firms” ([55] [56] [57] [58] [59]). Therefore, automation boosts incomes for capital owners, executives, managers and skilled professionals in these companies, thus amplifying top income inequality through returns on wealth, human capital, and management skills ([31] [60] [61] [62]).

Most of this evidence comes from high-income countries, while studies on developing economies are scarcer and less conclusive. For instance, de Vries et al. ([63]) document that robot adoption has reduced the employment share of routine manual task-intensive jobs in high-income countries, but not in developing economies. On one hand, automation could diminish the significance of low labor costs as a driver of international competitiveness, potentially hindering industrialization, participation in global value chains (GVCs), and export-led growth in developing countries, as production reshores back to high-income countries ([64] [65] [66] [67] [68] [69] [70]). On the other hand, robot adoption in high-income countries may increase imports from, and the number of affiliates in, low- and middle-income economies, aligning with the idea that offshoring and automation can be complementary ([41] [71] [44]). Moreover, if automation technologies exhibit diminishing returns, marginal productivity gains in developing countries—being at earlier stages of automation—could exceed those in industrialized economies ([53] [72] [73] [74] [75]). Should these gains translate into higher wages and greater demand for goods and services, the result could be faster economic growth, job creation, and improved welfare. However, these benefits may take time to materialize. For example, Brambilla et al. ([18]) find that robot adoption in major Latin American robot users (Mexico, Brazil, and Argentina) has displaced formal salaried jobs in the short run, particularly affecting young and middle-skilled workers, with informal employment acting as a buffer against rising unemployment.

Relatedly, evidence supports the notion that multinational companies (MNCs) promote technology diffusion and enhance the trade integration of host countries into the global economy ([75] [76] [77]). MNC investment, typically through inward foreign direct investment (FDI), can expand the production possibility frontier of host countries due to their adoption of more advanced technologies, including *industrial robots* ([78] [79] [80]), and higher productivity levels ([81] [82] [83] [84] [85]). Furthermore, MNCs have easier access to credit ([86] [87] [88]), greater product and process innovation ([89]), improved management practices ([90]), and greater reliance on high-skilled labor and capital than domestic firms ([91] [92] [93] [94] [95]).

Finally, recent evidence for the U.S. indicates that most current jobs have emerged from new specialties introduced since 1940, such as those in medicine and healthcare, personal care, recreation and entertainment, finance, software, and electronics, among others. Job creation initially focused on middle-income production and clerical occupations from 1940 to 1980 but has since shifted towards high-income professional jobs and, to a lesser extent, low-income service jobs since 1980 ([96]). These new jobs stem from technological advances that complement specific occupations, alongside demand shocks that heighten occupational demand. A*ugmentation* innovations boost occupational demand, while *automation* innovations often depresses it.[1] Notably, the authors find that while automation's demand-eroding effects have intensified over the past four decades, the demand-increasing effects of augmentation have not kept pace.

Importantly, new work typically (i) require expertise gained through formal education and/or practical experience, with the level of expertise varying across occupations, and (ii) represent the development of novel expertise or skills within existing jobs, rather than entirely new human endeavors.

## 4. Facts and discussion

### Basic determinants of automation

Figure 2 presents four scatterplots illustrating cross-country correlations between key determinants of automation and robot adoption between 1993 and 2022. One of the primary determinants of automation is GDP per capita (top panel 1). On the supply side, richer countries are more likely to develop and adopt new technologies, while firms in these economies are also incentivized to adopt automation to replace workers who receive higher wages than their counterparts in poorer nations. Supporting evidence indicates that rising wages and labor costs can drive firms to invest in automation technologies ([97] [98] [99] [100] [53]). On the demand side, firms in richer countries are more prone to automate and improve product quality to meet preferences of wealthier consumers, who have a greater willingness to pay for higher quality products. Second, as shown by Acemoglu and Restrepo ([40]), population aging is linked to increased industrial automation (top panel 2), as it creates a shortage of younger workers specialized in manual production tasks. Third, robot adoption is positively correlated with the average years of schooling within

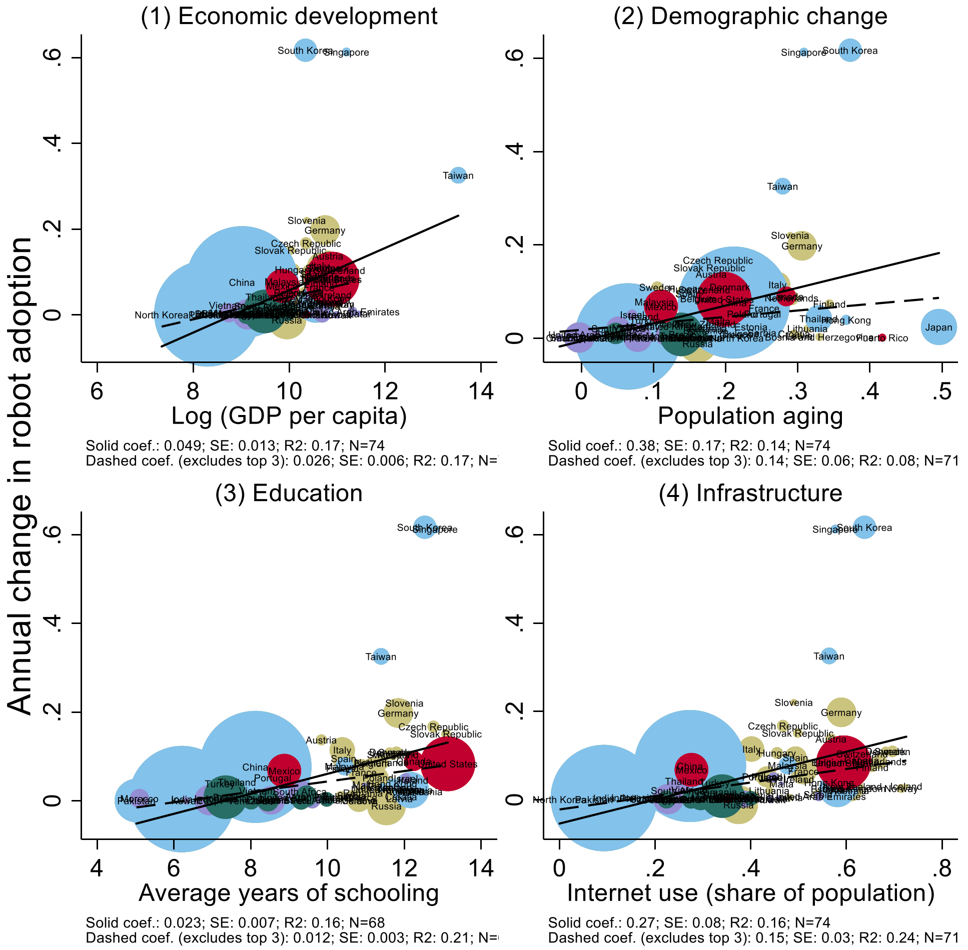
[1] *Augmentation* technologies increase capabilities, quality, variety or utility of the output of occupations, potentially leading to new demands for worker expertise and specialization; while *automation* technologies substitute for labor inputs in certain occupations, potentially replacing workers performing these tasks ([98]).

the labor force (bottom panel 3). A more educated population is more likely to innovate, adopt and work in complement with new technologies. Lastly, infrastructure, approximated by the percentage of the population with internet access (bottom panel 4), enhances the likelihood of adopting industrial robots, not only because many new technologies complement one another, but also because improved infrastructure boosts economic efficiency and market access.

Recent evidence suggests that greater integration into Global Value Chains (GVCs) is positively related to robot adoption, while rising automation simultaneously increases participation in GVCs, indicating bidirectional causality ([101]). Notably, this study finds that employment gains from automation are linked to deeper integration—both backward and forward—into GVCs. Additionally, growing robot adoption in an industry's export destinations is associated with increased robot adoption domestically, supporting a demand-driven explanation for automation. On the import side, industrial automation raises the demand for raw materials and standardized intermediate inputs, some of which are produced using industrial robots and traded via GVCs. On the export side, increased production at lower costs benefits from greater access to the global market, facilitated by deeper GVC integration. A related study finds that robotization in China spurred robot adoption in Europe through three main channels: an increased supply of intermediate inputs, rising market demand in China, and heightened import competition from Chinese firms ([102]).

On the microeconomic side, Acemoglu et al. ([54]) document that firms primarily invest in industrial robots to enhance process quality, upgrade existing operations, and automate tasks traditionally performed by labor, aligning with the evidence discussed in the previous section.

Figure 2. Leading determinants of automation



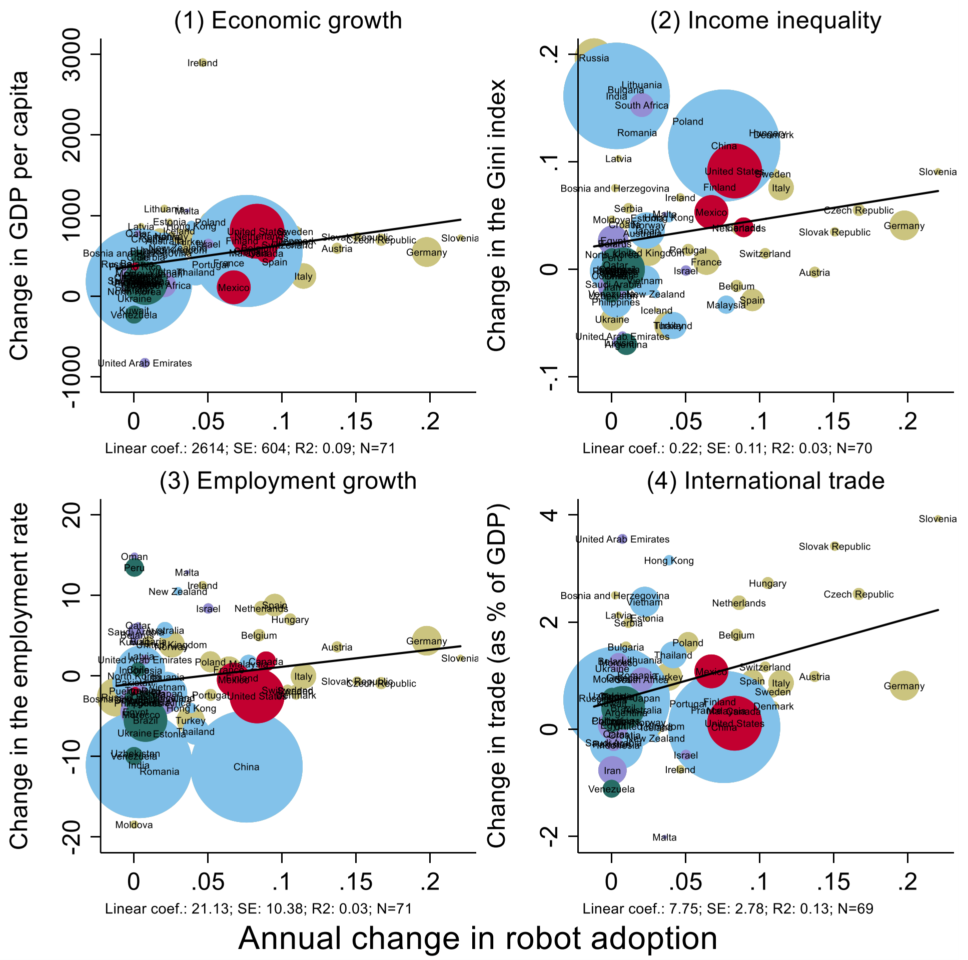

*Notes.* The y-axis measures the average annual change in the stock of robots per thousand workers in 1995 between 1993 and 2022. The x-axis correspond to: (1) the log average real GDP at constant USD 2017 PPP prices during 1993-2022; (2) the change in the ratio of old-age (+56) to middle-age (21-55) population between 1990 and 2020; (3) the average years of education for adults (15-64) during 1993-2022; and (4) the average fraction of population with access to internet connection during 1993-2022. The solid line depict the linear unweighted correlation between the y-axis and the x-axis; and the dashed line depicts the same correlation but excluding the top 5 percent countries with highest adoption of robots (i.e. Singapore, South Korea and Taiwan). Sources: IFR, OECD Employment data, UN World Population Prospects, and WDI (World Bank).

## Likely consequences of automation

The previous section examined much of the literature focused on the effects of automation on the labor market. This section provides a summarizing argument to emphasize some of the main likely consequences of industrial automation. Figure 3 presents four scatterplots illustrating cross-country correlations between robot adoption during 1993-2022 and changes in relevant economic outcomes over the same period. Top panel 1 shows that countries with relatively higher robot adoption exhibit experienced a greater annual increase in GDP per capita, consistent with evidence linking automation to productivity gains and rising production. Additionally, top panel 2 shows that countries adopting more robots exhibit an increase in income inequality, as indicated by changes in the Gini index, aligning with findings that robots tend to replace (manual and routine) middle-wage occupations while complementing professional and high-wage roles such as engineers, executives, managers, and capital owners.

Interestingly, bottom panel 3 illustrates a positive correlation between robot adoption and long-run changes in employment rates, suggesting that productivity growth translates into employment gains, i.e., reinstatement effects outweigh displacement effects. This indicates that the labor market adjusts to new working environments driven by advanced technologies, with most workers finding roles that complement new technologies. Lastly, bottom panel 4 shows that countries with higher robot adoption exhibit greater participation in international trade (as a share of GDP), consistent with the evidence that automating firms increase both their imports—mainly of intermediate inputs—and exports–mostly final products-, due to productivity gains and lower quality-adjusted prices, which enhance their competitiveness not only domestically but internationally.

Figure 3. Likely consequences of automation




*Notes.* The x-axis measures the average annual change in the stock of robots per thousand workers in 1995 between 1993 and 2022. The y-axis correspond to: (1) the average annual change in real

GDP at constant USD 2017 PPP prices during 1993-2022; (2) the change in the gini coefficient between 1990-1993 and 2018-2022; (3) the change in the employment to population ratio between 1990-1993 and 2018-2022; and (4) the average annual change in the trade to GDP ratio during 1993-2022. The solid line depict the linear unweighted correlation between the y-axis and the x-axis. Figures exclude the top 5 percent countries with highest adoption of robots (i.e. Singapore, South Korea and Taiwan). Sources: IFR, OECD Employment data, World Inequality Database, and WDI (World Bank).

## 4. Concluding remarks

The Third and Fourth Industrial Revolutions, primarily spanning from 1980 to the present, have fundamentally reshaped the global economic landscape. This new technological paradigm has introduced vast opportunities for economic progress while simultaneously presenting significant challenges, particularly regarding the future of work, income distribution, and potential environmental impacts.

This era is defined by breakthroughs in numerous fields, including information and communication technologies, the internet, biotechnology, renewable energy, industrial robotics, artificial intelligence, nanotechnology, quantum computing, big data, and 3D printing. These advancements are reshaping industries and labor markets worldwide.

The main conclusion of this review is that, while technological progress has not posed a significant threat to overall employment levels, it has unequivocally contributed to rising income inequality. Consequently, while a future without jobs is unlikely, the prospect of widespread equality remains uncertain.

Achieving shared prosperity will depend on the workforce's ability to adapt to the evolving demands of the labor market and on the equitable distribution of productivity gains stemming from new technologies. This necessitates a transformation in education systems, ensuring that individuals are equipped with the skills to work alongside new technologies throughout their careers. Lifelong learning will enable workers to capitalize on automation in routine tasks and leverage cognitive and abstract tasks that emphasize teamwork, problem-solving, flexibility, creativity, and social intelligence.

Furthermore, productivity growth driven by technological advancements will likely increase demand for both traditional and new goods and services, leading to income gains and heightened demand for quality. This dynamic will contribute to deeper structural changes, with an increasing share of the workforce engaged in service provision.

Importantly, the scale of production expansion enabled by certain technologies, particularly industrial robots, risks exacerbating resource depletion and environmental challenges by driving down prices, boosting consumption, and heightening demand for inputs and non-renewable raw materials. These developments necessitate a rethinking of resource management and environmental protection, especially in countries with weaker regulatory frameworks.

In light of these challenges, it is imperative for societies to allocate more resources to science and education. This investment will help create a more equitable global workforce, empowering individuals to harness the benefits of technological progress while remaining mindful of their environmental impact for the benefit of current and future generations.

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