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Artificial intelligence, services globalisation and income inequality

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Abstract

How does economic activity related to artificial intelligence (AI) impact the income of various groups in an economy? This study, using a panel of 86 countries over 2010–19, finds that investment in AI is associated with higher income inequality. In particular, AI investment is tied to higher real incomes and income shares for households in the top decile, while households in the fifth and bottom decile see a decline in their income shares. We also find a positive association with exports of modern services linked to AI. In labour markets, there is a contraction in overall employment, a shift from mid-skill to high-skill managerial roles and a reduced labour share of income.

Keywords: artificial intelligence, automation, services, structural shifts, inequality

JEL classification: D31, D63, O32

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1. Introduction

In modern economies, artificial intelligence (AI) is a force to be reckoned with.[1] AI systems are increasingly able to meet or surpass human capabilities in a growing number of specific tasks – from the game Go to image recognition to complex prediction. As such, they are being applied across various economic sectors. Some argue that this will serve as a powerful engine for overall productivity gains and global economic growth, lifting all boats (McKinsey Global Institute, 2021). Others perceive AI as highly dangerous, posing threats to humanity due to its potential for exponential improvement and unintended effects (Barratt, 2013; Bostrom, 2014). In light of recent breakthroughs in AI, such as the emergence of powerful large language models (LLMs) like ChatGPT[2] and so-called generative AI,[3] the potential economic impact has become increasingly apparent.

Among the most hotly debated aspects of AI adoption is its relationship with income inequality. In particular, cutting-edge AI technologies have the potential to disrupt various industries, leading to shifts in the labour market, skill requirements and income distribution. Already, simple applications of AI have been used for several years across a range of industries (McElheran et al, 2023). These help to optimise business decisions (eg on credit applications), support commerce (eg product recommendations), automate customer service (eg chatbots), improve production (eg robotic process optimisation) and more. Yet until now, very little is known about how AI-related economic activity is associated with changes in the real income of different groups of societies – the richest, the middle class, and the poorest – or why.

This paper provides empirical evidence on AI-related economic activity and changes in the income shares of different sub-segments of society in a global sample. Specifically, we examine the link between AI investment, incomes for different income deciles and other economic indicators in a panel of 86 economies around the world over 2010–19. We use a variety of new data sources about private investment in AI across countries and sub-sectors from Capital IQ, Crunchbase and Netbase Quid, as assembled for the Stanford AI Index. We combine this with detailed data on trade in goods and services from the UN COMTRADE and the IMF Balance of Payments, and with income distribution and labour market data from UNU-WIDER, World Bank PovcalNet, the Luxembourg Income Study (LIS), the OECD, the Standardised World Income Inequality Database (SWIID) (Solt, 2020) and the International Labor Organization (ILO). With this, we examine the differential changes in incomes as AI investment has risen over the last decade.

Underlying our analysis are at least four potential mechanisms by which AI adoption could influence income shares and income inequality. A first is the potential for AI to drive structural transformation of the economy, in particular a shift to high-productivity modern services. If this mechanism holds, then we may see higher production and incomes in the modern services sector, while incomes elsewhere do not change. This would result in higher inequality. A second mechanism is skill-biased technical change (Acemoğlu, 2002), or types of technological development that favour skilled workers. This bias can arise due to the adoption of skill-complementary (rather than skill-replacing) technologies. If AI adoption works in this way, a result would be higher incomes for skilled workers across different sectors. A third mechanism is greater market concentration, whereby successful firms (eg those that apply AI techniques) are able to rapidly gain market share at the expense of others, thus benefiting the owners (and potentially workers) of such firms. Each of these mechanisms would tend to link AI adoption with higher inequality. By contrast, a fourth mechanism is that AI substitutes for tasks traditionally performed by highly skilled or qualified labour, thus

1 AI can be defined as the design and building of intelligent agents that receive precepts from the environment and take actions that affect that environment (Norvig and Russel, 2020). This view of AI brings together a number of distinct subfields such as machine learning, big data analytics, computer vision, speech processing, natural language understanding, reasoning, knowledge representation and robotics, with the aim of achieving an outcome that would otherwise require the use of human intelligence. For alternative definitions see eg OECD (2019), FSB (2017), Microsoft (2022) and Google (2022).

2 ChatGPT was developed by the research laboratory OpenAI and publicly released as a prototype in November 2022. GPT stands for generative pre-trained transformer.

3 Generative AI can be defined as a class of AI models that are able to generate content such as text, images and other media.

reducing skills premia. Relatedly, the predictive power of AI applications could facilitate entry by new (less capital-intensive) firms, which could reduce concentration. It could also substitute for specialised skills. Whether these mechanisms hold in practice is largely an empirical question.

Our results push firmly in the direction of AI being associated with higher income inequality to date.

First, AI investment is tied to higher real incomes and a higher income share for the richest decile (d10) across countries.

Second, it is associated with no change in real incomes, and a significantly lower income *share* for the bottom decile (d1). This is consistently statistically significant and robust. The middle decile (d5) sees a small increase in real incomes, but still an overall decline in income share. In terms of economic significance, a one-standard deviation change in AI investment per capita is associated with the growth of real income of the top decile (d10) by nearly USD 1,300 and their share in total national income rising by 0.1 percentage points in a five-year period. Similarly, a one standard-deviation increase in per capita AI investment is associated with a fall in income shares by around 0.05 percentage points for the bottom decile over the same period.

Third, among types of AI, we find an especially strong association with inequality for AI used in real estate, network technology and robots – which would align with explanations focusing on the role of mechanical tasks and "lower-level" services that AI can help to automate. Beyond this, we find that AI investment is correlated with broader shifts in the economy, in particular higher total factor productivity (TFP) and exports of modern services. This aligns with the potential of AI to contribute to the globalisation of modern services, like software and information services.

Fourth, we find a negative association between AI investment and employment relative to the population, and a shift from mid-skill to high-skill and managerial employment. We also find a reduction in the labour share of income.

Overall, our results seem to be consistent with structural transformation and skill-biased technical change resulting from those types of AI that have been adopted to date. While we cannot (yet) disentangle these mechanisms in a more conclusive manner, we do find a relative shift from manufacturing to modern (professional) services coinciding with greater AI investment and greater income inequality.

Certainly, we acknowledge the limitations of our empirical strategy, which is based on country-level data for a relatively short time period. Given the inherent limitations, we do not claim causality. Moreover, those forms of AI that have been adopted since 2010 may not be representative of the LLMs, generative AI and other models being adopted at the time of writing. Further research will be needed to better understand the mechanisms at play and to assess these for the range of countries in our sample. Nonetheless, we believe that this macro-level panel analysis provides useful overall insights that can give general insights and form the basis for further investigation.

Our analysis contributes to a growing literature on the impact of AI on the economy. Much of this is organised around discussion of potential positive and negative externalities of AI.[4] Regarding positive externalities, the use of AI could boost productivity, revenue growth and employment growth, and allow for cheaper inputs that benefit different sectors of the economy (Alderucci et al, 2019; Rock, 2019). Indeed, some have called AI the "new electricity" (Ng, 2017) or a "general purpose technology" that is poised to join the steam engine or the electric motor in driving innovation in many disparate areas (Brynjolfsson and McAfee, 2014; Brynjolfsson et al, 2017). AI adoption and its impact are differentiated across sectors of the economy (McKinsey, 2021; Mishra et al, 2021). The adoption of AI capabilities such as machine translation can improve economic efficiency, particularly in digital trade or e-commerce platforms (Brynjolfsson et al, 2018). Yet these authors argue that the full effects of AI may not be realised until waves of complementary

[4] Externalities are costs or benefits caused by one economic actor that accrue to another. As one example, where AI directly replaces human labour, the demand for human labour may go down, along with wages (Korinek and Stiglitz 2020). Conversely, AI has led to an increase in demand for computer scientists and has greatly increased their wages.

innovations are developed and implemented; hence the productivity impact of software services may show up in economic statistics after a lag of a decade or more (Brynjolfsson et al, 2017). Similarly, the consumer surplus and welfare gains of digital technologies like AI may not be captured by economic statistics like GDP (Brynjolfsson et al, 2019). As an example, "free" services such as online maps and photo recommendation algorithms may be recorded in national accounts, but their value for consumers is not explicitly captured in economic statistics (Varian, 2018). There is evidence that AI job posting growth (a proxy of AI activity) is associated with higher output growth and subjective well-being, especially when the pre-existing industrial structure had a higher concentration of modern (or professional) services (Makridis and Mishra, 2022). Thus, AI could create opportunities for the future, but it may not yet be fully reflected in GDP accounting or other aggregate measurements (Mishra et al, 2020b).

The potential negative externalities of AI growth relate especially to the distributional impact of AI adoption, to market concentration and to related societal harms. Notably, AI research and development is relatively centralised, being driven by large corporations and governments in just a few jurisdictions. AI and automation could contribute to greater wage dispersion (Goldin, 2020). It has also been linked to manufacturing stagnation, a hollowing out of the middle class (Korinek and Stiglitz, 2021) and reduced demand for certain skills (Huang and Rust, 2018). One well-known study argues that nearly half of jobs in the US are at risk of being automated through computerisation (including AI) over the next decade or two (Frey and Osborne, 2017). Indeed, globalisation and automation are both credited with increasing income inequality in countries around the world.[5] AI technologies can complete tasks that could require human intelligence, either mechanical, thinking or feeling-based (Rust and Huang, 2021). AI has allowed for the automation not only of manual labour (eg industrial production), but increasingly of white-collar jobs in the services sector, eg translation services, data entry and paralegal work, to name only a few prominent examples. Some studies find that automation has been the primary driver in US income inequality over the past 40 years, with 50% to 70% of changes in U.S. wages since 1980 attributed to wage declines among blue-collar workers whose tasks were replaced or degraded (Acemoğlu and Restrepo, 2022).[6] This trend may have accelerated in the past few years.[7]

Our study adds to this work by assessing – based on aggregate, country-level data – how investment in AI correlates with economic outcomes. We provide high-level, cross-country evidence over a decade in which early forms of AI were increasingly adopted in economies around the world. With this, we provide useful evidence that can help inform further research with more disaggregated data.

The rest of the paper is organised as follows. Section 2 presents stylised facts to motivate our analysis. Section 3 presents the theoretical mechanisms, the diverse sources of data and our empirical approach. Section 4 presents our findings. Section 5 concludes with a discussion policy implications and avenues for future research. A technical appendix provides more details about the data sources.

[5] For example, some industry reports claim that robots will replace 200,000 jobs in the banking Industry by 2030 (Kelly, 2019), or that self-service kiosks have already led to fewer hourly workers at McDonald's (Rensi, 2018). AI could even impact high-tech jobs, with the goal of latest AI technologies to "write the software itself over time" (Dorsey, 2020). Key references in the literature on the impact of trade and financial globalisation on inequality are Feenstra and Hanson (1996) and Claessens and Perotti (2007). Jaumotte et al (2013) find that technological progress has had a greater impact on inequality than trade globalisation for 51 countries over 1981-2003. In a similar vein, there is evidence that AI-related scientific research is converging between the high income and upper middle-income countries, but a widening gap is developing that segregates the lower middle and low-income regions from the higher-income regions (Mishra and Wang, 2021).

[6] More generally, the use of AI on consumers' personal data has been link to privacy violations, while applications in news and media have been tied to an erosion of political discourse (Acemoğlu, 2021).

[7] For instance, during the first two years of the Covid-19 pandemic, the wealth of the world's ten richest men more than doubled, from USD 700 billion to USD 1.5 trillion, while the incomes of 99% of humanity fell (Oxfam International, 2022). This can be linked in part to the strong performance of global equity markets, particularly for AI-intensive technology companies. The impact of previous shocks is more nuanced. For example, the 2008 global financial crisis stopped the exceptionally fast income growth of the richest people in the world without perceptibly affect convergence of mean country incomes (Milanovic, 2022).

2. Stylised facts

Our analysis is motivated by three stylised facts visible in our combined data set. First is rapid progress in AI capabilities, resulting from technical progress in data availability, models and compute capabilities. This is also highlighted by the growing industrialisation of AI, with cost reductions in model training and a rapid growth of AI investment across countries. Second is the changing structure of global production, with a stagnation in the movement up the value chain from low-tech to high-tech manufacturing across countries. Third is the growing role of service exports, and specifically modern (professional) services that are increasingly embodied in technology infrastructure underpinning the global economy.

Growth and development of AI

Progress in AI is being driven by the availability of large volumes of structured and unstructured data, modelling and computing capabilities. The adoption of AI can be understood as a quality-adjusted drop in the cost of prediction (Agrawal et al, 2018; 2019), which can in turn allow powerful new applications. Technical progress in AI has mainly been measured – and driven – by comparing the performance of algorithms in specific prediction tasks according to different metrics across publicly-available challenge datasets. In many specific tasks, AI has surpassed human capabilities – a "John Henry moment" in which, like in the classic American folk tale, the machine overtakes the man (or woman).[8]

The image classification task of the ImageNet Challenge asks machines to assign a class label to an image based on the main object in the image. Top-5 accuracy asks whether the label is correct in at least the classifier's top five predictions. Graph 1 (left-hand panel) shows that the Top-5 accuracy rate has improved from around 85% in 2013 to almost 99% in 2020.[9] As shown in the right-hand panel, the training time on ImageNet has fallen from 6.2 minutes (December 2018) to 47 seconds (July 2020). At the same time, the amount of hardware used to achieve these results has increased dramatically; frontier systems have been dominated using "accelerator" chips, starting with graphical processing units (GPUs) in the 2018 results, and transitioning to Google's Tensor processing units (TPUs) for the best-in-class results from 2019 and 2020. The cost to train ImageNet to over 90% accuracy has fallen from over USD 2,000 to substantially less than USD 10 within the last three years (right-hand panel; Perrault et al, 2019 and Zhang et al, 2021).

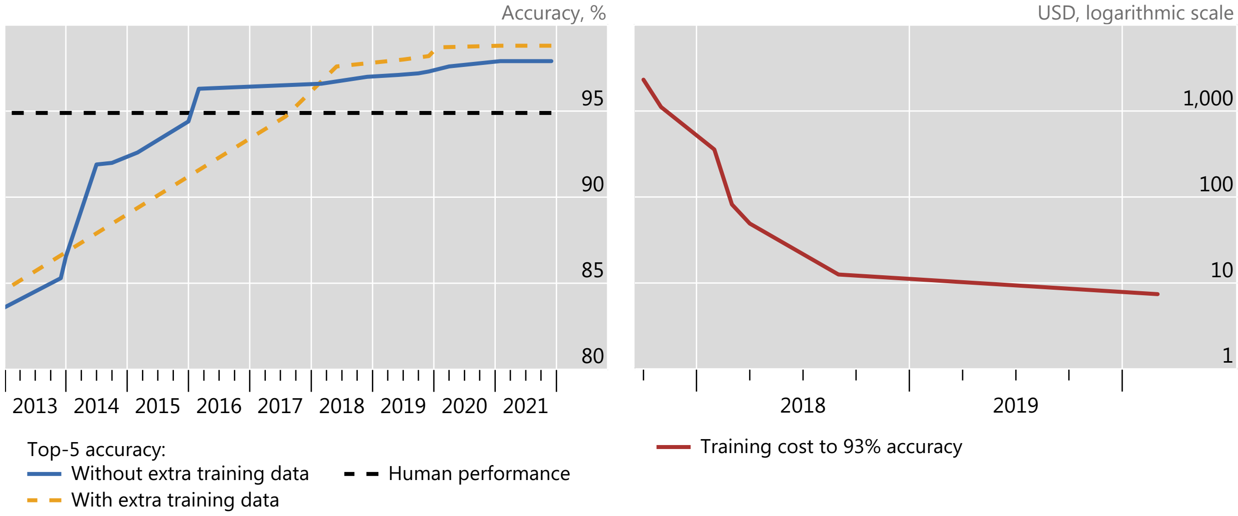
8 In the American folk ballad, John Henry is a railroad worker whose tools are a hammer and steel. He famously challenges a steam drill in a competition, and out-performs the machine before tragically dying. The legend can be seen as a parable for the struggle of human workers to keep up with advances in technology. The "John Henry moment" is the episode in which technology surpasses human capabilities in a specific task.

9 For data on human error, a human was shown 500 images and then was asked to annotate 1,500 test images; their error rate was 5.1% for Top-5 classification. This is a very rough baseline, but it gives us a sense of human performance on this task.

AI has achieved major breakthroughs in specific tasks as costs fall Graph 1

The "John Henry" moment: technical progress in AI, ImageNet challenge

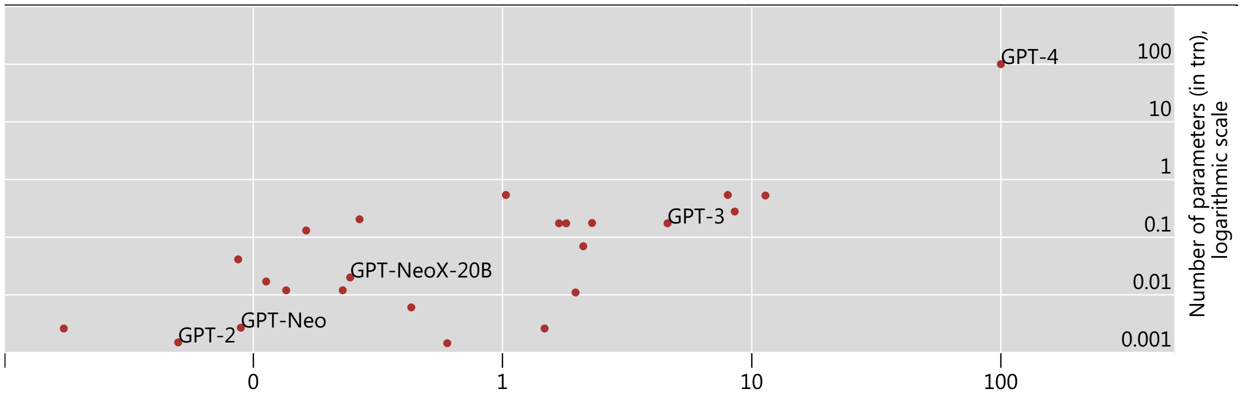
Reduction in training costs (to 93% accuracy) for ImageNet challenge



Sources: Paperswithcode, arXiv papers, MLPerf, DAWNBench, Stanford AI index report 2022.

Some of the more popular AI models are large neural networks that run on state-of-the-art machines. For example, AlphaGo Zero and Generative Pre-trained Transformer 3 (GPT-3) require millions of dollars in AI compute. This has led to state of AI research being dominated and shaped by a few actors that are mostly affiliated with large technology firms (big techs) or elite universities (Ahmed and Wahed, 2020). More recently, GPT-4 had a training cost close to USD 100 million, and required 100 trillion parameters (Graph 2). The exponential growth in computational power has led to astonishing improvements in AI capabilities, but it also raises questions of inherent inequality in compute capabilities. Greater attention is warranted to the unequal access to computational power – which has been a large contributor to recent improvements in model performance in fields such as natural language processing (NLP) – as well as the energy consumption and environmental cost associated with training computationally complex models.

Estimated training cost and number of parameters of selected AI models Graph 2

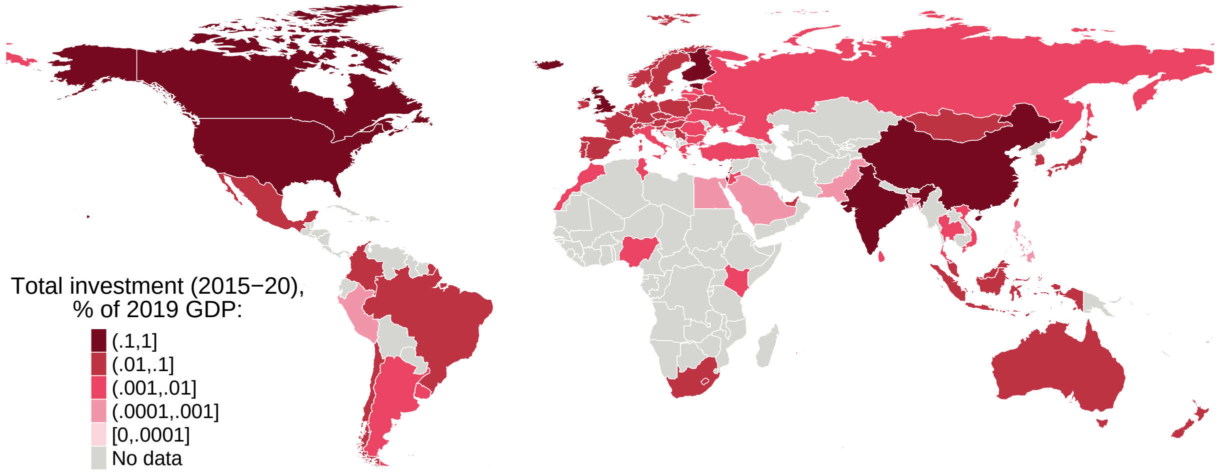


The precise training costs for AI models, particularly GPT-4 and Google BARD, remain largely undisclosed and are not officially documented with some available knowledge on their parameter counts. The figures, where applicable in the chart above, derive from available yet unverified sources or are approximations. It is imperative to acknowledge that various models may deploy different architectures, training data and compute infrastructure resources, affecting their respective training costs and parameter size. Furthermore, recent developments in the AI landscape, including innovative models and open-source approaches (not reflected in the graph), are potentially achieving comparable efficacy to the aforementioned models but with reduced model sizes and training costs. This reflects the swift progress in the field, diminishing both time and expenditure to achieve similar outcomes, with notable examples such as Llama2, Bloom, and the new Falcon 40b.

Sources: Epoch; Stanford 2023 AI Index; authors' calculations.

In our period of analysis, AI was increasingly adopted across a range of different sectors, especially by larger firms (McElheran et al, 2023). Internationally, AI investment was relatively concentrated in certain jurisdictions, particularly in North America, Europe, China and India. We measure global AI private investment with data from Capital IQ, Crunchbase and NetBase Quid. Private investment includes corporate AI investment, such as public offerings, mergers and acquisitions (M&A) and minority stakes related to AI. Private investment in AI has grown rapidly, reaching nearly 1% of GDP over the period 2015–20 (graph 3). Despite the pandemic, 2020 saw a 9.3% increase in the volume of private AI investment relative to the previous year. This growth was an acceleration relative to the 5.7% increase in 2019, though still shy of the 59% growth rate observed in 2018.

Total private investment in AI, 2015–20 Graph 3



The use of this map does not constitute, and should not be construed as constituting, an expression of a position by the BIS regarding the legal status of, or sovereignty of any territory or its authorities, to the delimitation of international frontiers and boundaries and/or to the name and designation of any territory, city or area.

Sources: IMF, *World Economic Outlook*; Capital IQ, Crunchbase, NetBase Quid; authors' calculations.

Structural shifts in production

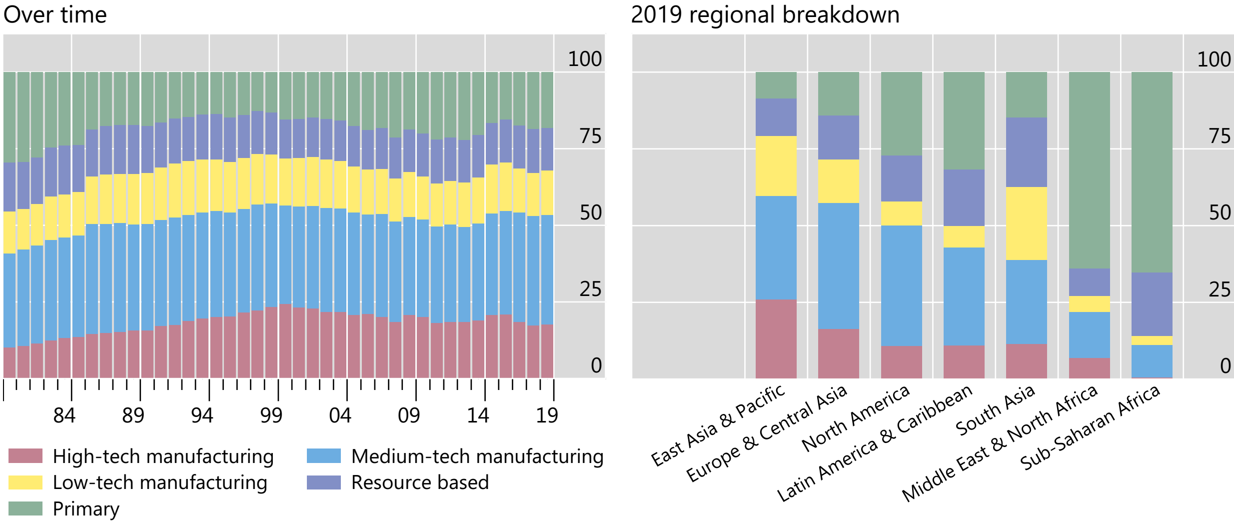
Meanwhile, the technology content of global production has shifted, as visible in detailed trade data. The data show that: (i) there is a relative stagnation in global production in physical goods, as the share of high-tech manufacturing in goods exports has stopped growing; and (ii) high-tech modern service exports are the fastest growing sector in global trade, helping to drive economic growth.

The relative stagnation in manufacturing has been a global phenomenon. To document this, graph 4 (left-hand panel) plots the average share of merchandise (goods) exports across income stage with regard to technological content. Over 1980–2000, there was a shift from primary into high-tech related manufacturing. Yet since then, the share of high-tech manufacturing has stayed roughly flat. Globally, within goods, there has been limited transition from primary production to high-tech manufacturing over the last four decades. While regions differ starkly in the breakdown of their goods exports (right-hand panel), the changes in such shares since 2000 have been limited.

At the same time, technological changes have made manufacturing more capital and skill-intensive (Ghani et al, 2016) creating fewer jobs than in past decades. In many developing countries, some form of premature deindustrialisation seems to have set in (Rodrik, 2015; Cadot and Gourdon, 2016). Indeed, in African economies, manufacturing – the sector that led rapid development in East Asia – is declining as a share of GDP. The worry is that without a major transformation, developing countries' recent growth spurt may soon run out of steam (Ghani and O'Connell, 2014). Globalisation and labour-saving technological progress in manufacturing have been behind technological development, with many scholars highlighting that premature deindustrialisation has potentially significant economic and political ramifications. These could include lower economic growth and democratic failure (Rodrik, 2015). Yet manufacturing is not the only game in town to drive growth and development in the coming decades.

Stagnation in goods exports and limited transition to tech-intensive manufacturing

In per cent Graph 4



The graph shows temporal and regional breakdown of global merchandise exports for a sample of 180 countries.

Sources: Lall (2005); UN COMTRADE, SITC Rev. 3; authors' calculations.

AI as a service and structural shifts

Especially advanced economies have experienced significant changes in the structure of output since World War II. Initially driven by a move from agriculture to manufacturing (Herrendorf et al, 2014), technological change led to a rise in the digital workforce in the manufacturing and services sectors (Gallipoli and Makridis, 2018). Coupled with the rise of globalisation (Rodrik, 2018), the rise of digital technologies led to an exodus of workers from manufacturing to (high-tech) services. Importantly, the modernisation of the services sector saved it from dragging down aggregate GDP – at least in the United States (Gallipoli and Makridis, 2018), where services were traditionally known for having lower productivity growth, ie "Baumol's cost disease" (Baumol, 1967).

Emerging technologies like AI are changing the characteristics of services. Indeed, service activities can be unbundled, disembodied and splintered in a value chain, just like goods (Bhagwati, 1984). Such technological changes are driving up demand for complex technology-intensive services. The virtual capabilities of this class of services, such as being transported cheaply and swiftly in binary bits, makes it more desirable than goods (Mishra et al, 2020a).

We refer to modern services, such as AI, information technology or research and development, and distinguish these from traditional, non-professional or low-tech services like haircuts, restaurants or tourism that require face-to-face contact and more manual labour (Baumol, 1967; Ghani and Kharas, 2010). Modern services such as AI are digitally intensive and intangible (Mishra et al, 2021). Similar to high value-added manufacturing, modern services may yield greater knowledge spillovers, have a greater potential for backward and forward linkages or offer an easier pathway toward discovering new specialisations with similar characteristics (Anand et al, 2012; Loungani et al, 2017).[10]

Historically, buyers and sellers needed to meet face to face. Yet many modern services can be carried out in one location and consumed in many other places. The internet and other systems of network

[10] We will also use this split in our regressions below. Of course, the distinction between traditional and modern services may be subject to definitional questions. In future work, this could form an additional robustness check.

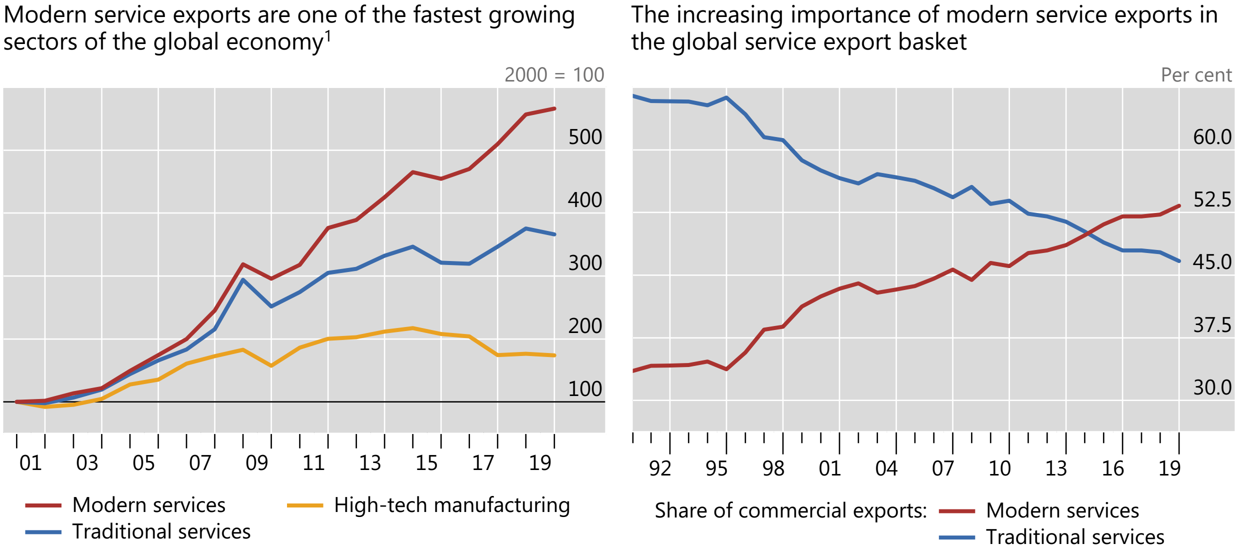
technologies like industrial robotics and AI are providing technical changes to production techniques and business processes. For example, machine translation systems have significantly increased international trade on online platform, increasing exports by 10.9% driven by substantial reduction brought about by translation costs (Brynjolfsson et al, 2019).

Graph 5 (left-hand panel) shows components of world exports – modern services, traditional services and high-technology manufacturing exports, with the year 2000 indexed to 1. The chart shows that modern service exports have grown five-fold since 2000, whereas high-technology manufacturing exports are declining. Similarly, the right-hand panel shows the structural shift within global services exports between modern and traditional services.

The process of structural change can lead to growing inequality. Our paper builds on an empirical literature in economics that uses data on inequality to understand social welfare (Kahneman and Deaton, 2010; Deaton, 2012), and responds to calls for more research on the relationship between AI and income inequality (Musikanski et al, 2020). In this way, we contribute to the ongoing debate about AI and its implications for various income groups in society.

The rise of modern services

Graph 5



[1] Modern services include research and development, business services, computer and information services and financial intermediation. Traditional services include construction, transport and tourism. High-tech manufacturing includes automatic data processing equipment, telecom equipment and office machines.

Sources: IMF, *BPM6*, 2022; authors' calculations.

3. Theoretical mechanisms, data and empirical approach

How could these shifts in the economy lead to changes in incomes and income inequality? We distinguish between four potential mechanisms: (i) structural transformation, (ii) skill-based technical change; (iii) market concentration and (iv) AI substituting skilled or qualified labour.

The first of these is structural transformation, in particular the shift to modern services. In classical economic theory, an economy's growth potential lies in its innate capabilities that are rooted in its production structure. This can be attributed to the early ideas that viewed growth and development as a process of structural transformation in the productive structure of the economy (Lewis, 1955; Hirschman, 1958; Kuznets and Murphy, 1966; Kaldor, 1967), ie the reallocation of resources from low-productivity to high-productivity activities. Services are typically viewed as a low-productivity sector, and a passive input into the production of physical goods. Emerging technologies like AI are changing the characteristics of services. Service activities can be unbundled, disembodied and splintered in a value chain just like goods (Bhagwati, 1984). These ideas were originally pioneered at the onset of the modern services revolution as manufacturing began to decline in developed countries, although many questions remain (Karmarkar, 2004; Karmarkar and Apte, 2007; Karmarkar et al, 2015). Furthermore, rapid urbanisation and growth in city clusters, characteristic of emerging cities, can reduce demand for physical goods and increases demand for services. Agglomeration and economics of scale in service cities are incentivising service hubs of exports even across US cities (Berube, 2007), like factory-driven industrialisation in Asian economies. The old idea of services being non-transportable, non-tradable and non-scalable no longer holds for a range of modern impersonal services like AI. Similar to the invention of the steam engine and the cotton gin, inequality was probably pushed up by the movement of people from the countryside into cities – to more productive, more diverse (and hence more unequally paid) jobs (Milanovic, 2016). As AI is increasingly adopted, this could further promote this structural shift, thus benefiting the (high-tech) services sector, owners of such firms and service sector workers, while incomes in other sectors may be unaffected (see Mishra et al, 2011; Mishra et al, 2020a).

A second mechanism is skill-biased technical change. Acemoğlu (2002) argues that over the 20th century, the rapid increase in the supply of skilled workers was accompanied by skill-complementary (rather than skill-substituting) technologies. These tended to increase the wage premium for skilled workers. AI could lead to further manifestations of this trend, as those workers able to apply AI – such as computer programmers, data scientists and other professionals – increase their productivity and capture larger wage shares. Indeed, while real median wages in many advanced economies have stagnated in recent years, there has been substantial wage growth for AI researchers (see eg https://aipaygrad.es). A similar trend is visible for wages in the technology sector more generally, which have outstripped the economy as a whole and the financial sector (Pereira Da Silva et al, 2019). If this mechanism holds, then one would expect higher wages for skilled workers in sectors across the economy.

A third mechanism is market concentration. As discussed above, AI research is heavily concentrated in a few jurisdictions, and also among relatively few institutions and firms who can afford to attract the needed talent and pay for the (ever-increasing) compute costs needed for cutting-edge AI. In the economy as a whole, those firms able to keep up and invest in these technologies may have a heavy advantage over their competitors who cannot do so. AI could thus be tied to the success of "superstar firms", which have high mark-ups and a lower labour share of valued added (Autor et al, 2021). If this mechanism holds, then one may expect to see higher incomes of the owners of such firms, with the impact on wages being more ambiguous. Overall, this mechanism would still be consistent with greater inequality after AI adoption.

A fourth mechanism goes in the opposite direction, with AI substituting for skilled or qualified labour. This is reflected in some recent worries about large language models like ChatGPT, whose written output may be (initially) indistinguishable from the output of a human expert. It is also consistent with criticism of the direction of AI research in recent years. The famous Turing test for whether a machine is intelligent has led AI researchers and businesses to focus on building machines to replicate human intelligence (Turing, 1950; Brynjolfsson, 2022).[11] Yet this obsession with mimicking human intelligence has led to AI and automation that too often simply replace workers, rather than extending human capabilities and allowing people to do new tasks (Brynjolfsson, 2022; Rotman, 2022).

Which of these mechanisms is important in practice is largely an empirical question. In this light, we move to our data and empirical approach.

[11] The Turing test is derived from the "imitation game" of Alan Turing and assesses whether a computer can imitate a person so well that the receiver cannot distinguish between the computer versus a human.

Data sources

We use a variety of data sources to help shine light on the nexus between AI activity and income inequality. Country-level data on private sector AI investment come from Capital IQ, Crunchbase and Netbase Quid, and serve as proxies of overall AI activity by country. To study sub-sector-specific AI growth, we use data from Netbase Quid for 49 AI sub-sectors that we manually curate to obtain 39 AI sub-sectors.

The trade data for physical goods come from UN COMTRADE (https://comtrade.un.org). The specific technology intensity of manufacturing is described below. The data on service exports are from the IMF Balance of Payments. The data on inequality (Gini coefficient), income and income share by decile come from UNU WIDER, Povcal Net, World Bank, OECD Inequality database and the Solt (2020) database for various robustness tests. For our control variables, we use data from the World Bank World Development Indicators, Bank for International Settlements (BIS), UN and the International Monetary Fund (IMF). Labour market outcomes come from the International Labor Organization (ILO). The details about each data source and related caveats are documented in the appendix.

Table 1 gives descriptive statistics of our key series. Recent developments around AI started to achieve economic relevance in some countries around 2010. For instance, big data analytics became more widely used for prediction in business processes, robotic process automation started to gain traction and retail AI applications such as matching algorithms for e-commerce started to take off in this period. For this reason, our sample of analysis covers the period 2010–19 and 86 countries, of which 36 are advanced economies, and 50 are emerging market and developing economies (see Annex table A3).

Descriptive statistics Table 1

	Observations	Mean	Std. dev.	Min	Max
Total factor productivity (TFP)	617	0.99	0.06	0.83	1.44
Real GDP per capita ('000 USD)	701	27.04	18.74	0.98	96.81
Exports of services (% of nominal GDP)	701	12.95	15.88	0	92.33
Exports of modern services (% of nominal GDP)	667	6.45	15.87	0	132.79
Exports of traditional services (% of nominal GDP)	667	7.77	6.74	0	29.38
Manufacturing exports (% of nominal GDP)	701	2.56	1.83	0	9.06
Ln(Gini index)	701	37.50	8.56	15.16	72.88
Mean income of 1st decile	701	7,457	6,283	137.87	28,139
Mean income of 5th decile	701	21,915	16,216	863.68	86,255
Mean income of 10th decile	701	75,624	47,234	7,631	262,981
Income share of 1st decile	701	2.34	0.86	0.45	4.09
Income share of 5th decile	701	7.28	1.07	3.11	8.86
Income share of 10th decile	701	29.05	6.70	20.25	53.17
Investment in artificial intelligence[1]	701	5.10	13.67	0	65.01
Investment in AI for real estate / insurtech[1]	701	0.04	0.20	0	1.13
Investment in AI for fintech[1]	701	0.28	0.88	0	3.71
Investment in AI for retail[1]	701	0.09	0.34	0	1.81
Investment in AI for network technology[1]	701	0.03	0.12	0	0.61
Investment in AI for robots[1]	701	0.17	0.48	0	2.20
Trade openness	701	97.07	66.31	22.49	381.52
Share of government consumption in real GDP at current PPPs	701	0.19	0.06	0.05	0.35
UN education index	701	0.76	0.13	0.33	0.93
Domestic banking credit to private sector as a share of GDP	701	70.46	44.56	8.15	217.54
Foreign direct investment, net inflows (% of GDP)	701	5.98	12.77	–11.68	80.99

The full dataset covers 113 countries, of which 22 advanced-economies, and the period 2009–20, subject to data availability.

[1] Five-year rolling sum of investments in the specific AI vertical divided by population in each given year. Figures are expressed in USD per capita.

Sources: IMF; UNU-WIDER, *World Income Inequality Database (WIID)*; AI investment data; United Nations; World Bank; authors' calculations.

Empirical approach

With these data, we are able to assess how incomes, income shares and other variables have changed as AI investment has risen over the past decade.

The analysis is conducted in three steps. First, we explore the relationship between AI investment, income inequality and the income distribution by decile. Second, we examine the relationship of AI investment with TFP, output per capita and sectoral allocations. Third, we look at developments in labour markets, which can help us understand the channels by which AI investment may be associated with changes in the income distribution.

The empirical analysis in the first step is based on the following specification:

$$d_{n,i,t} = \gamma_1 \left(\frac{AI_{INV}}{POP}_{i,t}\right) + \beta_1 \ln(H_{i,t}) + \beta_2 \ln(\frac{CREDIT}{Y}_{i,t}) + \beta_3 (TO_{i,t}) + \beta_4 (CSGH_{i,t}) + \beta_5 (FDI_{i,t}) + \propto_i + \theta_t + \varepsilon_{n,i,t}$$

where $d_{n,i,t}$ is the target, either the natural logarithm of the Gini coefficient, the real mean income level or the share of total income by decile *n* in a given country *i* in year *t*. The variable $\frac{AI_{INV}}{POP}_{i,t}$ denotes AI investment in the previous 5 years in country *i* divided by the population in year *t*. We have added additional covariates to our baseline regressions, based on the specifications of Jaumotte et al (2013) for inequality. However, we have been more selective in the inclusion of controls. We use: $\ln(H_{i,t})$, the natural logarithm of the UN Education Index; $\ln(\frac{CREDIT}{Y}_{i,t})$, the natural logarithm of domestic bank credit to the private sector divided by GDP; $TO_{i,t}$, trade openness, or the sum of exports and imports divided by GDP; $CSGH_{i,t}$, the share of government consumption to GDP at current purchasing power parity; $FDI_{i,t}$., foreign direct investment net inflows as a share of GDP; and $\propto_i$.and θ_t denote country- and year- fixed effects, respectively.

In the second and third steps, we use a similar set of controls, but with alternative dependent variables such as TFP and output (second step) or labour market outcomes (third step).

It is important to highlight the limitations and uncertainties associated with the empirical strategy used in this paper when it comes to accurately identifying the underlying mechanisms behind the observed patterns, including:

- Limited time period: the ten-year panel data may not fully capture the long-term implications of AI investment on income inequality. The short timeframe could potentially miss out on observing the more profound and longer-lasting effects of AI on the economy, labour markets and income distribution. The latest era of rapid AI development (since 2020) is not accounted for.
- Causality and endogeneity: our empirical strategy does not allow for assessing causal relationships between AI investment and income inequality. As such, the results must be interpreted as correlations rather than causation. Endogeneity issues, such as omitted variable bias or reverse causality, might also confound the relationship between AI investment and income inequality.
- Heterogeneity: the macroeconomic approach may not account for heterogeneity across countries and AI subsectors, possibly leading to aggregated results that might not fully reflect the diverse experiences of individual countries or specific AI applications.
- Measurement error: the proxy variables used for AI investment and income inequality may not perfectly capture the true extent of these phenomena. The data sources and construction of these variables may introduce measurement errors, which could affect the empirical results.

- Unobserved factors: our empirical strategy may not be able to control for all relevant factors that may influence income inequality, leading to omitted variable bias. The inclusion of additional controls, such as capital flows or non-AI technological progress, might be needed to account for these potential confounding factors.[12]

4. Empirical results

Our empirical results are presented in the following order. First, we show the relationship between AI investment and income inequality. Second, we assess the link between AI investment and broader economic outcomes including sectoral allocation. Third, we show the interaction with labour markets.

AI and income inequality

How do overall income inequality, and the incomes of different segments in society, vary with private AI investment? Table 2 provides the results.

Column I shows that the Gini coefficient is significantly higher (at the 99% confidence level) when AI investment is higher. For a one standard deviation increase in AI investment per capita, the natural logarithm of the Gini index increases by roughly 0.2% of the sample average. This is roughly the difference between the average log Gini index of eg the Unites States and Uruguay. Among deciles, we find that the lowest decile sees no statistically significant change in income; the middle decile sees a USD 370 increase, and the highest decile sees USD 1,300 more income on average (columns II-IV). The coefficients are significant also from an economic perspective. Looking at column IV, the USD 1,300 income increase for the top income decile corresponds to almost 2% of the mean, or the difference in average GDP per capita of New Zealand and Israel. (This is twice the difference in incomes between Spain and Cyprus). When looking at shares, the lowest income decile sees their income share fall by 0.05 percentage points, and the middle decile by 0.02 percentage points. By contrast, the upper decile sees incomes increase by 0.1 percentage points (columns V-VII). From an economic perspective, the magnitudes of these effects are not large, but they are also not negligible. A one standard deviation increase in AI investment corresponds to a drop of around 2% (first income decile), a drop of 0.3% (middle decile), and an increase of 0.35% (upper decile) of the respective sample means. In all specifications, we use country and year fixed effects, achieving a high r-squared. As the sample of analysis includes data for 86 countries and 10 years, we do not have enough granularity to use double-clustering (see Thompson, 2011). For this reason, we cluster standard errors by time to account for serial correlation.[13] The statistical significance and magnitudes are robust to a broader set of controls.

[12] We report pairwise correlations for the independent variables used in our empirical analysis in table B1 in the appendix. Results show that correlations among in our set of controls is modest (ie almost always below 0.3).

[13] By clustering standard errors by time, we implicitly allow for arbitrary correlation between observations in the ten time periods, and consequently, that there are ten uncorrelated observations. Conversely, clustering by country would have implied assuming that there are 86 uncorrelated observations, a considerably less stringent assumption.

Investments in artificial intelligence and inequality Table 2

	Ln(Gini index)	Mean income of decile[1]			Income share of decile		
		1st decile	5th decile	10th decile	1st decile	5th decile	10th decile
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
Investment in artificial intelligence[2]	0.0005** (0.0002)	3.9219 (3.4269)	26.6876*** (7.3494)	95.9699*** (19.1851)	–0.0032** (0.0011)	–0.0014** (0.0005)	0.0075* (0.0040)
Controls[3]	Y	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	701	701	701	701	701	701	701
R-squared	0.9806	0.9846	0.9944	0.9911	0.9603	0.9844	0.9838

Standard errors clustered by time in brackets; ***/**/* indicates statistical significance at the 1/5/10% level.

[1] Based on 2017 PPP USD. [2] The independent variables is a five-year rolling sum of investments in AI divided by population in each given year. [3] Controls are trade openness, the share of government consumption in real GDP at current PPPs, the UN Education index, the domestic banking credit to private sector as a share of GDP, and FDI net inflows as a share of GDP.

Sources: UNU-WIDER, *World Income Inequality Database (WIID)*; AI investment data; United Nations; World Bank; authors' calculations.

Within AI investment, certain types of AI seem to have a more significant relationship with income distributional changes (Table 3). For example, AI for real estate / insurtech may be associated with higher incomes for those active in these markets. Real estate professionals use standardised data through multiple listing services (MLS) to perform easier search and matching through marketplaces (eg with online platforms like Zillow or Redfin); this could benefit high-income professionals, thus leading to positive correlation between prices and sales (see eg Gabrovski and Ortego-Marti, 2021). Similarly in the insurance industry, in-car sensors can track driving behaviour for determining insurance premiums (Soleymanian et al, 2019), which could allow AI-intensive firms to more accurately price risk, earn higher returns and capture a larger share of the market. These relatively straightforward use cases for AI in the past decade may have been associated with particularly large changes in the relative incomes of different groups. Results from table 3 show that a one standard deviation increase in AI investment per capita in this sector is associated with an increase in the Gini coefficient of about 0.7%, a rise in the income share of the top income decile by 0.5% and a drop in the income share of the lowest income decile by close to 2%.

Meanwhile, AI for network technology also shows a strong positive relationship with inequality, given lower real incomes for the bottom decile and higher top income shares. A similar pattern is visible for AI for robots. This would be consistent with these types of AI substituting for unskilled labour and thus driving job loss for lower-income households. AI investment in fintech is associated with higher incomes for the top decile, which could be consistent with financial technology disproportionately benefiting more sophisticated or higher-wealth clients (see Frost et al, 2022). Interestingly, AI in retail (which could include Ai applications supporting personalised buying recommendations or cash registers) is not associated with higher inequality to date. Results from table 3 show that a one standard deviation increase in AI investment per capita in this sector is associated with an increase in the Gini coefficient of about 0.3%, an increase of the size of 1.5% of the mean of the top income decile and a drop close to 1.5% of the mean of the share of the lowest income decile. Conversely, results for the lowest income decile and the share of the top income decile are not statistically significant.

Similarly, AI for robots shows a positive relationship with inequality. This would be consistent with the use of robotic process automation by some firms, which may yield high profits and high wages for those (few) specialists able to operate such systems. A one standard deviation increase in AI investment in this field corresponds to an increase in inequality (ie Gini index) of about 0.7%, an increase of about 3% of the mean of the mid- and top income decile respectively, and a drop of close to 2% of the mean in the income share of the lowest-income decile.

Results for AI investment in fintech and in retail yield very similar findings. For the former, a one standard deviation increase in AI investment in this field corresponds to an increase in the Gini coefficient of about 0.6%, and an increase of about 1.5% of the mean of the middle and top income deciles. It is tied to a drop of close to 2% of the mean of the share of the lowest income decile. For the latter, a one standard deviation increase in AI investment in this field corresponds to an increase in the Gini coefficient of about 0.15%, an increase of about 2% of the mean of the top income decile, and a drop close to 1% of the mean of the share of the lowest income decile.

Differences across sectors may reflect how exactly AI is being applied in each case. Some observers delineate "mechanical AI" for standardisation, "thinking AI" for personalisation and "feeling AI" for relationalisation (Rust and Huang, 2021). Mechanical tasks may be easier for AI to automate, particularly for repetitive and routine tasks where a high volume of market data is available, as in manufacturing. Compared with the mechanical-based segmentation, thinking-based AI (as in real estate or insurance) could help to process big data to arrive at decisions. Feeling AI was not yet widely adopted in this period, but it could be more important in the future. Of course, as these types of AI are applied more intensively in different sectors, the association with income shares may change further.

Investments in artificial intelligence verticals and inequality

Table 3

	Ln(Gini index)	Mean income of decile[1]			Income share of decile		
		1st decile	5th decile	10th decile	1st decile	5th decile	10th decile
	(I)	(II)	(III)	(IV)	(V)	(VII)	(VIII)
Investment in AI for	0.0328***	-393.6**	995.4***	5266.9***	-0.2430***	-0.0273	0.5739***
real estate / insurtech[2]	(0.0039)	(145.3)	(130.3)	(947.5)	(0.0190)	(0.0200)	(0.1334)
Controls[3], FE	Y	Y	Y	Y	Y	Y	Y
Observations	701	701	701	701	701	701	701
R-squared	0.9807	0.9847	0.9943	0.9911	0.9607	0.9843	0.9838
Investment in AI for	0.0287*	18.3	2272.3**	8549.1**	-0.2538**	-0.0257	0.3489
network technology[2]	(0.0128)	(590.4)	(722.6)	(3086.0)	(0.0992)	(0.0562)	(0.3371)
Controls[3], FE	Y	Y	Y	Y	Y	Y	Y
Observations	701	701	701	701	701	701	701
R-squared	0.9804	0.9846	0.9943	0.9911	0.9600	0.9843	0.9837
Investment in AI for	0.0144**	249.3	1174.1***	5025.5***	-0.0900***	-0.0444**	0.2892*
robots[2]	(0.0046)	(181.6)	(259.8)	(1067.9)	(0.0232)	(0.0156)	(0.1370)
Controls[3], FE	Y	Y	Y	Y	Y	Y	Y
Observations	701	701	701	701	701	701	701
R-squared	0.9806	0.9847	0.9946	0.9917	0.9602	0.9844	0.9839
Investment in AI for	0.0067**	-16.4	325.1153**	1219.7***	-0.0508***	-0.0119	0.1108
fintech[2]	(0.0030)	(59.9)	(129.0)	(333.4)	(0.0150)	(0.0103)	(0.0711)
Controls[3], FE	Y	Y	Y	Y	Y	Y	Y
Observations	701	701	701	701	701	701	701
R-squared	0.9806	0.98	0.9944	0.9911	0.9605	0.9843	0.9838
Investment in AI for	0.0042**	226.6*	1059.1***	3601.5***	-0.0519*	0.0040	0.0526
retail[2]	(0.0016)	(100.3)	(222.2)	(461.7)	(0.0280)	(0.0158)	(0.0904)
Controls[3], FE	Y	Y	Y	Y	Y	Y	Y
Observations	701	701	701	701	701	701	701
R-squared	0.9803	0.9847	0.9945	0.9912	0.9597	0.9843	0.9837

Standard errors clustered by time in brackets; ***/**/* indicates statistical significance at the 1/5/10% level. All regressions include country and year fixed effects.

[1] Based on 2017 PPP USD. [2] The independent variables are a five-year rolling sum of investments in the specific AI vertical divided by population in each given year. [3] Controls are trade openness, the share of government consumption in real GDP at current PPPs, the UN Education index, the domestic banking credit to private sector as a share of GDP, and FDI net inflows as a share of GDP.

Sources: UNU-WIDER, *World Income Inequality Database (WIID)*; AI investment data; United Nations; World Bank; authors' calculations.

Overall, the findings in this first step could be consistent with theory and other evidence that the gains of AI are captured by a small group of highly skilled workers, professionals or large corporations.[14] Yet they do not allow us to disentangle the mechanisms.

AI investment, services and economic output

We next turn to the relationship with services and economic output. Table 4 summarises the results.

Here, we find AI investment is associated with higher total factor productivity (TFP) (column I). It is also associated with higher real GDP per capita (column II). There is a notable shift in economic structure. Data on overall service exports and the technological sophistication of service exports (available for 2010–20) show a striking pattern. While overall services do not increase (column III), exports of modern services do (column IV). Traditional services see no significant change (column V) and manufacturing exports actually decline (column VI). Our findings are significant also from an economic perspective. A one standard deviation increase in investment in AI per capita corresponds to an increase of about 1% of the mean of TFP, 5% of the mean of real GDP per capita, 20% of the mean of exports of modern services and a decrease of nearly 7% of the mean of manufacturing exports.

Investment in artificial intelligence and economic structure

Table 4

	TFP	Real GDP per capita ('000 USD)	Exports of services (% of nominal GDP)	Exports of modern services (% of nominal GDP)	Exports of traditional services (% of nominal GDP)	Manufacturing exports (% of nominal GDP)
	(I)	(II)	(III)	(IV)	(V)	(VI)
Investment in artificial Intelligence[1]	0.0006***	0.0964***	–0.0496	0.0845***	0.0052	–0.0102***
	(0.0001)	(0.0133)	(0.0847)	(0.0106)	(0.0073)	(0.0030)
Controls[2]	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	829	1038	1172	936	936	1172
R-squared	0.4666	0.9916	0.8909	0.9790	0.9354	0.8425

Standard errors clustered by time in brackets; ***/**/* indicates statistical significance at the 1/5/10% level.

[1] The independent variables is a five-year rolling sum of investments in AI divided by population in each given year. [2] Controls are trade openness, and FDI net inflows as a share of GDP.

Sources: IMF, *World Economic Outlook*; University of Groningen, *Penn World Table*; UNU-WIDER, *World Income Inequality Database (WIID)*; AI investment data; authors' calculations.

Over time, AI may be capable of performing even the intuitive and empathetic tasks, enabling innovative ways of human-machine integration that are impacting the largest sector of the global economy – services (Huang and Rust, 2018; 2021). Scholars have extolled the impact the industrialisation of services for decades, with outsourcing and offshoring being only part of the revolution (Bhagwati, 1984; Blinder, 2006; Karmarkar, 2004). The use of computationally intensive data processing, big data and AI may

[14] Rising productivity at the global frontier is coupled with an increasing productivity divergence between the global frontier and laggard firms (Andrews et al, 2015; Goyal and Aneja, 2020). At the global level (considering world citizens irrespective of border) disparities have declined somewhat due to the fast growth of the middle class in emerging markets (Lakner and Milanovic, 2016). It is an open question how these disparities will develop going forward.

be even more pronounced in the coming years as AI-based services are applied in many industries, including education, retail, human resources, marketing, customer engagement and manufacturing.

AI investment and employment

Our third step is to look at how AI investment has correlated with aggregate employment across the economy, the employment shares of different sectors and the employment shares of different types of workers based on skills. We have data on these indicators from the ILO database ILOSTAT.

Results of a first set of regressions are presented in table 5. Strikingly, we find AI investment to be associated with lower employment relative to the population (column I). This result is strongly statistically and economically significant; a one-standard deviation shock in AI investment corresponds to a drop of more than 1% of the mean of the dependent variable. We do not see large shifts across the agriculture, industry or services sectors as suggested by the statistically insignificant coefficients from columns II-IV.

Investments in artificial intelligence, and labour market

Table 5

	Employment to population[1]	Employment share		
		Agriculture	Industry	Services
	(I)	(II)	(III)	(IV)
Investment in artificial Intelligence[2]	–0.022*** (0.0060)	0.004 (0.0042)	–0.006 (0.0050)	–0.009 (0.0063)
Controls[3]	Y	Y	Y	Y
Country FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	569	560	569	569
R-squared	0.982	0.960	0.944	0.955

Standard errors clustered by time in brackets; ***/**/* indicates statistical significance at the 1/5/10% level.

[1] Ratio of total employment to population. [2] The independent variables is a five-year rolling sum of investments in AI divided by population in each given year. [3] Controls are trade openness, the share of government consumption in real GDP at current PPPs, the UN Education index, the domestic banking credit to private sector as a share of GDP, and FDI net inflows as a share of GDP.

Sources: ILOSTAT; UNU-WIDER, *World Income Inequality Database (WIID)*; AI investment data; United Nations; World Bank; authors' calculations.

When looking at employment shares by skill, we do find important differences. Table 6 reports the results. While the employment share of low-skill workers does not show a significant association with AI investment (column I), we do find a strongly statistically significantly lower employment share of mid-skill employment in countries and years with strong investment in AI (column II). From an economic perspective, a one standard deviation increase in investment in AI per capita corresponds to a drop of about 1.5% of the mean of the employment share of mid-skill employment. Meanwhile, there is also a significantly higher employment share of higher-skill workers and managers (columns III-IV). A one standard deviation increase in the independent variable is associated with an increase of 1.5% and 2.5% of the mean of the respective dependent variable. This is consistent with skill-biased technical change, where high-skilled workers and managers benefit disproportionately when new AI applications are developed and adopted. Finally, we find a lower labour share of income in countries and years with higher AI investment, significant at the 90% level (column V). This drop is the flip side of a higher share of capital in income during the period of analysis (Piketty et al, 2018), particularly in economies with high AI investment. In terms of magnitudes, a one standard deviation increase in the dependent variable is associated with a drop of more than 0.5% of the mean of the labour share of income.

Investments in artificial intelligence, and labour market Table 6

	Employment share				Share of labour compensation in GDP
	Low skill[1]	Mid skill[2]	High skill[3]	Managers	
	(I)	(II)	(III)	(IV)	(V)
Investment in	–0.008	–0.024***	0.027***	0.007**	–0.0002*
artificial Intelligence[4]	(0.0095)	(0.0064)	(0.0047)	(0.0027)	(0.0001)
Controls[5]	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Observations	569	569	569	565	647
R-squared	0.969	0.938	0.957	0.971	0.962

Standard errors clustered by time in brackets; ***/**/* indicates statistical significance at the 1/5/10% level.

[1] *Craft and related trades workers*, *Plant and machine operators, and assemblers*, and *Elementary occupations*, as defined in the ILOSTAT data. [2] *Clerical support workers*, *Service and sales workers*, and *Skilled agricultural, forestry and fishery workers*, as defined in the ILOSTAT data. [3] *Professionals*, and *Technicians and associate professionals*, as defined in the ILOSTAT data. [4] The independent variables is a five-year rolling sum of investments in AI divided by population in each given year. [5] Controls are trade openness, the share of government consumption in real GDP at current PPPs, the UN Education index, the domestic banking credit to private sector as a share of GDP, and FDI net inflows as a share of GDP.

Sources: ILOSTAT; UNU-WIDER, *World Income Inequality Database (WIID)*; AI investment data; United Nations; University of Groningen, *Penn World Table*; World Bank; authors' calculations.

Overall, we find that AI investment is associated with higher incomes for the top decile and thus with higher inequality. It is also associated with higher TFP and higher output, and with a growth of high-tech services exports. While we do not claim causality based on this methodology, we believe these results help to shed light on possible mechanisms by which AI may have impacted the income distribution to date.

This is also consistent with some micro-level evidence. For instance, AI-related innovations are found to be positively associated with firm growth as firms with AI-related innovations have 25% faster employment growth and 40% faster revenue growth than a comparative set of firms (Alderucci et al, 2019). Similarly, the launch of TensorFlow is associated with an approximate market value increase of USD 11 million per 1 percent increase in AI skills for AI-using firms (Rock, 2019). AI superstar firms in the top quintile (exporting software and information services firms) appear to benefit more than less intensive adopters. Our findings on employment shares tend to support the idea that high-skilled workers and managers benefit disproportionately when AI applications are implemented. In combination with our results on high-tech services exports, this leans toward a role for AI investment as a specific manifestation of skill-based technical change. Further research will be needed to corroborate these findings.

5. Conclusion

AI is a powerful force in modern economies, whose impact across sectors is only beginning to be understood. In this study, we have explored the link between AI investment and income inequality. We have shown that, in a global panel, especially higher-income households have seen their incomes and income shares increase, while lower-income users have seen a reduction in income shares after AI investment. We show that AI investment is also associated with greater productivity and a shift to high-tech services, which can often be traded across borders. We see lower employment and a shift from mid- to high-skill and managerial jobs, as well as a decline in the labour share of income.

Of course, it is too early to say whether the increase in inequality in economies with high AI investment is merely transitory or will have longer-lasting effects. While automation and a move toward high-tech services can lead to displacement of workers in the near term, it may create new opportunities over time that may not yet be visible in our sample. Indeed, there may also be effects on subjective well-being beyond incomes that are not visible in output data.

Much of the longer-term impact will also depend on public policies, which could help smooth transitions across sectors and cushion the blow of lost incomes of affected households and regions. Public policy could even play a role to reduce the divides in access to data, models and computing power within and across countries. For example, more equal access to standardised and scalable data infrastructure to inform AI use cases, building inherent skills through training across the AI value chain through tertiary education and online learning, and public investment efforts help make cloud compute resources accessible for universities and research centres could help to bridge the digital divide. This could counteract some of the current imbalances in the AI sector, itself, from spatial concentration of AI activity, underrepresented women in AI research, or the inherent bias and fairness issues associated with building AI systems. Differentiated policy interventions should be designed given the position of a country in the AI ecosystem and the role of specific AI sectors in the production chain (Ernst and Mishra, 2021).

Our study is unable to shed light on these policies or their relative effectiveness. Yet given the likelihood that AI development will continue to advance, it seems prudent to better understand these effects and design public policies accordingly. AI is a highly interdisciplinary field and studying the intersection of AI and inequality should be viewed as the same. Accounting for human aspects, especially the impact on well-being of the production, distribution, delivery and consumption of AI systems will remain pertinent to comprehensively studying AI and inequality.

Future research can consider the following avenues. First, it could extend the analysis to a longer time period (including more recent, higher-frequency data) or incorporate time lags to better capture the long-term effects of AI investment on income inequality. Second, it may employ alternative econometric techniques, eg instrumental variable regressions, difference-in-differences or synthetic control methods, to mitigate endogeneity concerns and establish causal relationships. Third, it could examine the impact of AI investment on income inequality at a more disaggregated level, considering individual countries or specific AI subsectors. Fourth, researchers may work to improve the measurement of AI investment and income inequality by using alternative data sources or building more accurate proxy variables. Fifth, it could incorporate additional control variables that may influence income inequality to account for unobserved factors and reduce omitted variable bias. These approaches may hold great promise to better understand the causal impact of a technology that is set to become more important over time.

References

Acemoğlu, D (2002), “Technical Change, Inequality and the Labor Market”, *Journal of Economic Literature*, vol 40, pp 7–72.

--- (2021), “Harms of AI”, National Bureau of Economic Research (NBER) working paper no 29247.

Acemoğlu, D and P Restrepo (2022), “Tasks, Automation, and the Rise in US Wage Inequality”, *Econometrica*, vol 90, pp 1973–2016.

Alderucci, D, L Branstetter, E Hovy A Runge and N Zolas (2019), “Quantifying the Impact of AI on Productivity and Labor Demand: Evidence from U.S. Census Microdata”, *mimeo*.

Ahmed, R and M Wahed (2020), "The De-democratization of AI: Deep Learning and the Compute Divide in Artificial Intelligence Research", arXiv preprint arXiv:2010.15581.

Agrawal, A, J Gans and A Goldfarb (2018), *Prediction machines: the simple economics of artificial intelligence*, Cambridge, MA: Harvard Business Press.

--- (2019), “Economic policy for artificial intelligence”, *Innovation Policy and the Economy*, vol 19, pp 139–159.

Andrews, D, C Cirscuolo, and P Galthe (2015), “Global Productivity Slowdown, Technology Divergence and Public Policy: A Firm level Perspective”, OECD Background Paper.

Anand, R, S Mishra and N Spatafora (2012), “Structural Transformation and the Sophistication of Production”, *IMF Working Paper*, no 12/59, February.

Autor, D, D Dorn, L Katz, C Patterson and J van Reenen (2020), “Fall of the labor share and superstar firms”, The Quarterly Journal of Economics, vol 135, no 2, pp 645–709.

Barratt, J (2013), *Our Final Invention: Artificial Intelligence and the End of the Human Era*, New York: Thomas Dunne Books.

Baumol, W (1967), “Macroeconomics of unbalanced growth: the anatomy of urban crisis”, *American Economic Review*, vol 57, no 13, pp 415–26.

Berube, A (2007), "Metro nation: How U.S. metropolitan areas fuel American prosperity", *Blueprint for American Prosperity*, The Brookings Institution.

Bhagwati, J (1984), “Splintering and Disembodiment of Services and Developing Nations”, *The World Economy*, vol 7, no 2, pp 133–44.

Blinder, A (2006), “Offshoring: The next industrial revolution?”, *Foreign Affairs*, vol 85, no 2, pp 113–28.

Bostrom, N (2014), *Superintelligence: Paths, Dangers, Strategies*, Oxford: Oxford University Press.

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

Brynjolffson, E, D Rock and C Syverson (2017), “Artificial Intelligence and the Modern Productivity Paradox: A Clash of Expectations and Statistics”, NBER Working Paper, no 24001.

Brynjolffson, E, A Collis, W Diewert, F Eggers and K Fox (2019), “GDP-B: Accounting for the Value of New and Free Goods in the Digital Economy”, NBER Working Paper no 25695

Brynjolfsson, E, X Hui and M Liu (2018), “Does machine translation affect international trade? Evidence from a large digital platform”, *NBER Working Papers*, no 24917, August.

Brynjolfsson, E (2022), “The Turing Trap: The Promise & Peril of Human-Like Artificial Intelligence”, *Daedalus*, Spring.

Cadot, O and J Gourdon (2016), "Non-tariff measures, preferential trade agreements, and prices: new evidence", *Review of World Economics* (Weltwirtschaftliches Archiv), vol 152, issue 2, no 1, 227–49.

Claessens, S and E Perotti (2007), "Finance and Inequality", *Journal of Comparative Economics*, vol 35, no 4, pp 748–73.

Clifford, C (2020), "Twitter billionaire Jack Dorsey: Automation will even put tech jobs in jeopardy", CNBC, 22 May.

Deaton, A (2012) "International Journal of Community Well-Being", *Oxford Economic Papers*, vol 64, no 1, pp 1–26.

Ernst, Ekkehard and S Mishra (2021), "AI Efficiency Index: Identifying Regulatory and Policy Constraints for Resilient National AI Ecosystems", SSRN.

Feenstra, RC and GH Hanson (1996), "Globalization, Outsourcing, and Wage Inequality", *American Economic Review*, vol 86, no 2, pp 240–5.

Frey, C and M Osborne (2017), "The Future of Employment: How Susceptible Are Jobs to Computerisation?" *Technological Forecasting and Social Change*, vol 114, pp 254–80.

Frost, J, L Gambacorta and R Gambacorta (2022), "On the nexus between wealth inequality, financial development and financial technology", *Journal of Economic Behavior & Organization*, vol 202, pp 429–51.

Gabrovski, M and V Ortego-Marti (2021), "Search and credit frictions in the housing market", *European Economic Review*, vol 134.

Gallipoli, G and C Makridis (2018), "Structural transformation and the rise of information technology", *Journal of Monetary Economics*, vol 97, no C, pp 91–110.

Ghani, E and O'Connell (2014), "Can service be a growth escalator in low-income countries?", World Bank Policy Research Working Paper Series, no 6971.

Ghani, E, A Goswami, W Kerr (2016), Highway to Success: The Impact of the Golden Quadrilateral Project for the Location and Performance of Indian Manufacturing. Economic Journal, no 126, pp 317–57.

Ghani, E and H Kharas (2010), "The Service Revolution", *World Bank - Economic Premise*, no 14, pp 1-5.

Goldin, I (2020), *Technology and the future of work*. New York: New York University.

Goyal, A and R Aneja (2020), "Artificial intelligence and income inequality: Do technological changes and worker's position matter?", *Journal of Public Affairs*, vol 20, no 4.

Herrendorf, B, R Rogerson and A Valentinyi (2014), "Growth and Structural Transformation", in P Aghion and SN Durlauf (eds), *Handbook of Economic Growth*, Amsterdam: Elsevier.

Hirschman, AO (1958), *The Strategy of Economic Development*, New Haven: Yale University Press.

Huang, MH and R Rust (2018), "Artificial intelligence in service", *Journal of Service Research*, vol 21, no 2, pp 155–72.Jaumotte, F, S Lall and C Papageorgiou (2013), "Rising income inequality: technology, or trade and financial globalization?", *IMF Economic Review*, vol 61, no 2, pp 271–309.

Kahneman, D and A Deaton (2010), "High income improves evaluation of life but not emotional well-being", *Proceedings of the National Academy of Sciences*, vol 107, no 38, pp 16489–93.

Kaldor, N (1967), *Strategic factors in economic development*, Ithaca: Cornell University.

Karmarkar, U (2004), "Will you survive the services revolution?," *Harvard Business Review*, June.

--- (2015), "OM Forum- The service and information economy: Research opportunities," Manufacturing and Service Operations Management. https://doi.org/10.1287/msom.2015.0525.

Karmarkar, U and U Apte (2007), "Operations management in the information economy: Information products, processes, and chains", *Journal of Operations Management*, no 25. https://doi.org/10.1016/j.jom.2006.11.001.

Karmarkar, U, Kihoon Kim and Hosun Rhim (2015), "Industrialization, Productivity and the Shift to Services and Information", *Production and Operations Management*, no 24. https://doi.org/10.1111/poms.12379.

Kelly, J (2019), "Wells Fargo Predicts That Robots Will Steal 200,000 Banking Jobs Within The Next 10 Years", *Forbes*, 8 October.

Korinek, A and J Stiglitz (2021), "Artificial intelligence, globalization, and strategies for economic development", NBER working paper no 28453.

Kuznets, S and JT Murphy (1966), *Modern economic growth: Rate, structure, and spread*, New Haven, CT: Yale University Press.

Lakner, C and B Milanovic (2016), "Global Income Distribution: From the Fall of the Berlin Wall to the Great Recession", *The World Bank Economic Review*, vol 30, no 2, pp 203–32.

Lewis, W (1955), *The theory of economic growth*, London: Routledge.

Loungani, P, S Mishra, C Papageorgiou and K Wang (2017), "World Trade in Services: Evidence from A New Dataset", *IMF Working Paper*, no 2017/077, March.

Makridis, C and S Mishra (2022), "Artificial Intelligence as a Service, Economic Growth, and Well-Being", *Journal of Service Research*, vol 0, no 0.

McElheran, K, J Li, E Brynjolfsson, Z Kroff, E Dinlersoz, L Foster, N Zolas (2023): "AI Adoption in America: Who, What, and Where", NBER working paper no 31788, October.

McKinsey Global Institute (2021), "Global survey: The state of AI in 2021", December.

Microsoft (2022), "Artificial Intelligence (AI) Architecture Design", online at https://docs.microsoft.com/en-us/azure/architecture/data-guide/big-data/ai-overview, accessed 20 September.

Milanovic, B (2016), "Income Inequality is Cyclical", *Nature*, vol 537, no 7621, pp 479–82.

--- (2022), "After the Financial Crisis: The Evolution of the Global Income Distribution Between 2008 and 2013", *The Review of Income and Wealth*, vol 68, no 1, pp 43–73.

Mishra, S, S Gable and R Anand (2011), "Service Export Sophistication and Economic Growth", World Bank Working Policy Paper, WPS5606.

Mishra, S, I Tewari and S Toosi (2020a), "Economic Complexity and the Globalization of Services", *Structural Change and Economic Dynamics*, vol 53, no C, pp 267-280.

Mishra, S, J Clark, and C Perrault (2020b), "Measurement in AI Policy: Opportunities and Challenges", arXiv preprint arXiv:2009.09071.

Mishra, S, R Koopman, G De-Prato, A Rao, I Osorio-Rodarte, J Kim, N Spatafora, K Strier, and A Zaccaria (2021), "AI Specialization for Pathways of Economic Diversification", arXiv preprint arXiv:2103.11042.

Mishra, S and K Wang (2021), "Convergence and Inequality in Research Globalization", arXiv preprint arXiv:2103.02052.

Musikanski, L, B Rakova, J Bradbury, R Phillips and M Manson (2020), "Artificial Intelligence and Community Well-being: A Proposal for an Emerging Area of Research", *International Journal of Community Well-Being*, 3, pp 39–55.

Ng, A (2017), "AI is the new electricity", lecture to Stanford MSx Future Forum, 25 January.

Norvig, P and S Russell (2020), *Artificial Intelligence: A Modern Approach – 4th ed.*, Hoboken: Prentice Hall.

Oxfam International (2022), "Ten richest men double their fortunes in pandemic while incomes of 99 percent of humanity fall", January.

Pereira da Silva, L, J Frost and L Gambacorta (2019), "Welfare implications of digital financial innovation", speech, 20 November.

Perrault, R, Y Shoham, E Brynjolfsson, J Clark, J Etchmendy, B Grosz, T Lyons, Lyons, J Manyika, S Mishra and J Niebles (2019), "The 2019 AI Index Report", Stanford University Institute for Human-Centered Artificial Intelligence (HAI).

Piketty, T, E Saez, and G Zucman (2018), "Distributional national accounts: methods and estimates for the United States", *The Quarterly Journal of Economics,* vol 133, no 2, pp 553–609.

Rensi, E (2018), "McDonald's Says Goodbye Cashiers, Hello Kiosks ", *Forbes*, 11 July.

Rock, D (2019), "Engineering Value: The Returns to Technological Talent and Investments in Artificial Intelligence", SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3427412.

Rodrik, D (2015), "Premature Deindustrialization", NBER Working Paper 20935.

--- (2018), "New technologies, global value chains, and developing economies", NBER Working Paper 25164.

Rotman, D (2022), "How to solve AI's inequality problem", *MIT Technology Review*, April.

Rust, R and MH Huang (2014), "The service revolution and the transformation of marketing science," *Marketing Science*, 33. https://doi.org/10.1287/mksc.2013.0836.

--- (2021), "The Feeling Economy", The Feeling Economy, Springer International Publishing. https://doi.org/10.1007/978-3-030-52977-2.

Soleymanian, M, C Weinberg and T Zhu (2019), "Sensor Data and Behavioral Tracking: Does Usage-Based Auto Insurance Benefit Drivers?", *Marketing Science*, vol 38, no 1, pp 21–43.

Solt, F (2020), "Measuring income inequality across countries and over time: the Standardized World Income Inequality Database", *Social Science Quarterly*, vol 101, no 3, pp 1183–99, version 9.3 (June 2022).

Thompson, S B (2011), "Simple formulas for standard errors that cluster by both firm and time", *Journal of Financial Economics*, vol 99, no 1, pp 1–10.

Turing, A (1950), "Computing Machinery and Intelligence", *Mind*, LIX (236), pp 433–60.

Varian, H (2018), "Artificial Intelligence, Economics, and Industrial Organization", NBER Working Paper no 24839.

Zhang, D, S Mishra, E Brynjolfsson, J Etchemendy, D Ganguli, B Grosz, T Lyons, J Manyika, J Niebles, M Sellitto, Y Shoham, J Clark, and R Perrault (2021), "The AI Index 2021 Annual Report," AI Index Steering Committee, Human-Centered AI Institute, Stanford University, Stanford, CA, March.

Appendix A: data sources and preparation

Income inequality

Income inequality data come from the UNU-WIDER World Income Inequality Database (WIID).[15] In particular, we leverage the companion dataset that collects yearly statistics that UNU-WIDER data experts have aggregated at the country level. This dataset contains information for more than 195 countries with at least one observation between years 1940–2019. Although these series may originally refer to different welfare concepts (eg per capita consumption, total household gross income), they have been adjusted to consistently compare country-level series over time and across countries. The concepts covered include the Gini index, the mean income of each percentile of the population (from poorest to richest), their share as a percentage of the country total income and summary measures built using these quantities.

The measure of TFP comes from University of Groningen, *Penn World Table* and it corresponds to TFP at constant national prices (2017=1). We use data from the IMF, *Balance of Payments* and UN COMTRADE to measure the exports of services, modern services, traditional services and manufacturing. The data on trade openness comes from the World Bank and it is defined as the sum of exports and imports of goods and services measured as a share of gross domestic product. The data on the share of government consumption in real GDP at current PPPs, and on real GDP come from the Penn World Table. We use the education index from the United Nations which is an average of mean years of schooling (of adults) and expected years of schooling (of children), both expressed as an index obtained by scaling with the corresponding maxima. Finally, the data on domestic banking credit to private sector as a share of GDP come from the World bank and it is defined as financial resources provided to the private sector by other depository corporations (deposit taking corporations except central banks), such as through loans, purchases of nonequity securities, and trade credits and other accounts receivable, that establish a claim for repayment. The resulting series are then linearly interpolated over the full period (1990–2020).

Artificial intelligence investment

Data on private sector AI investment come from Capital IQ, Crunchbase and Netbase Quid. These serve as proxies of overall AI activity by country and year. To study sub-sector specific AI growth, we use data from Netbase Quid that originally provides data for 49 AI sub-sectors. We manually curate this to obtain 39 AI sub-sectors. We index 3.6 million public and private company profiles from multiple data sources indexed to search across company descriptions, while filtering and including metadata ranging from investment information to firmographic information such as year founded, headquarters location and more. Trends are based on reading the text description of companies to identify key words, phrases, people, companies and institutions; then comparing different words from each document (news article, company descriptions, etc) to develop links between these words based on similar language. This process is repeated to produce a network that shows how similar all documents are. AI investment is concentrated in select countries; for example, over 2019–20, North America accounted for 58% of global AI investment, followed by East Asia and Pacific (28%) and Europe and Central Asia (10%), with the Middle East and North Africa (2%), South Asia (1%), Latin America (0.5%) and Sub-Saharan Africa (0.2%) accounting for only very minor global shares. China alone accounted for approximately 20% of global AI investment in 2019–20.

Beyond AI investment, various indicators are available to measure AI research and development, investment and adoption. We follow Mishra et al (2021) in using the Netbase Quid data to segment investment in the following macro area AI investment sectors (table A1).

[15] UNU-WIDER, World Income Inequality Database (WIID) Companion dataset (wiidcountry and/or wiidglobal). Version 31 May 2021. https://doi.org/10.35188/UNU-WIDER/WIIDcomp-310521.

Macro area AI investment segmentation

Table A1

Macro area	Lower-level AI investment labels
AgriTech	Farming, Agricultural, Crop, Farmers
AR/VR	Augmented reality, Vr, Virtual reality, Ar
Data Management	Data center, Robotic process automation, Devops, Workloads Data scientists, Hadoop, Sql, Data science teams
EdTech	Students, Courses, Edtech, Language learning
Energy	Energy management, Renewable, Buildings, Electricity Oil, Downtime, Industrial internet, Failures Satellite, Water, Geospatial, Remote sensing
Facial Recognition	Facial, Weapons, Video surveillance, Law enforcement
Fintech	Bank, Spending, Gift, Debit Crypto, Trading platform, Decentralized, Traders Funds, Wealth management, Equity, Investing Loans, Lending, Lenders, Credit scoring
Legal, HR	Legal, Law, Document management, Contract management Recruiting, Candidate, Hiring process, Talent acquisition Workforce, Workplace, Hr, Career
Marketing, Content	Advertisers, Digital marketing, Marketers, Ads Music, Skin, Video editing, Photo editing
Medical	Cancer, Drug discovery, Molecular, Therapeutics Hospital, Physicians, Doctor, Clinical trials Medical imaging, Surgical, Ct, Radiology Neuroscience, Retinal, Artificial general intelligence, Eye tracking
Network Technology	Wireless, Wi fi, Parents, Wifi
Quantum, Semiconductor	Quantum, Computer peripheral devices, Integrated circuits, Quantum machine learning Semiconductor, Chips, Processor, Data centers
Real Estate, InsurTech	Commercial real estate, Estate agents, Landlords, Residential real estate Insurtech, Claim, Insurance industry, Insurance services
Retail	Fashion, Visual search, Shopping experience, Clothing Restaurants, Beverage, Ingredients, Kitchen Retail technology, Personalization, Shoppers, Merchandising
Robots, Bots	Chatbot, Bots, Conversational artificial intelligence, Messenger Industrial automation, Picking, Service robot, Defect Semantic, Articles, Topics, Language understanding
Sales, Customer Success	Customer support, Customer feedback, Customer satisfaction, Contact center Meetings, Productivity tools, Slack, Conferencing Sales automation, Sales teams, Prospects, Reps
Security	Data privacy, Data protection, Sensitive data, Gdpr Fraud detection, Identity verification, Money laundering, Anti fraud Threat, Network security, Attacks, Cybersecurity
Supply Chain	Supply chain management, Invoices, Procurement, Freight
Vehicle	Autonomous vehicles, Fleet, Cars, Autonomous driving Drone, Unmanned, Inspections, Unmanned aircraft
Wellness	Booking, Travelers, Hotels, Trip Fans, Esports, Athletes, Gamers Wellness, Chronic, Cardiac, Therapy

Source: authors' elaboration based on Netbase-Quid AI investment data reported in the Stanford 2021 AI Index.

Goods trade

Trade data are from UN COMTRADE (https://comtrade.un.org) for physical goods. Specific technology intensity of manufacturing is provided below.

Primary products (and special transactions, excluded completely below) do not need much analysis in terms of the technological basis of comparative advantage.

Within manufactured exports, the technological categories and sub-categories are as follows:

- **Resource-based (RB) products** tend to be simple and labour-intensive (eg simple food or leather processing), but there are segments using capital, scale and skill-intensive technologies (eg petroleum refining or modern processed foods). Since competitive advantages in these products arises generally – but not always – from the local availability of natural resources, they do not raise important issues for competitiveness. Yet the segments with skill and technology intensive technologies do raise important competitiveness issues. We draw a distinction between RB1, agriculture-based products and RB2, others.
- **Low-technology (LT)** products tend to have stable, well-diffused technologies. Technologies are primarily embodied in capital equipment; the low end of the range has relatively simple skills requirements. Many traded products are undifferentiated and compete on price: thus, labour costs tend to be a major element of cost in competitiveness. Scale economies and barriers to entry are generally low. The final market grows slowly, with income elasticities below unity. However, there are exceptions to these features. There are particular low technology products in high-quality segments where brand names, skills, design and technological sophistication are very important, even if technology intensity does not reach the levels of other categories. We should note that products of major interest to developing countries tend to be in the lower-quality segments, and are really based on simple technologies and price rather than quality competition. We distinguish between LT1, textile, garment, footwear ("fashion") cluster and the LT2, other low technology products. The former group has undergone massive relocation from rich to poor countries, with assembly operations shifting to low wage sites and complex design and manufacturing functions retained in advanced countries. This relocation has been an engine of export growth in this industry, though the precise location of export sites in textiles and clothing has been influenced strongly by trade quotas, eg under the Multi-Fibre Agreement as well as offshore assembly provisions and regional trade agreements like the North American Free Trade Agreement (NAFTA). Other exports that have benefited from active relocation in this group are toys, sports and travel goods and footwear. Simple metal products have not shared in this particular process, perhaps because they are not equally prone to undifferentiated mass-assembly operations, or because skill needs are somewhat higher.
- **Medium-technology (MT)** products, comprising the bulk of skill and scale-intensive technologies in capital goods and intermediate products, are the core of industrial activity in mature economies. They tend to have complex technologies, with moderately high levels of R&D, advanced skill needs and lengthy learning periods. Those in the engineering and automotive sub-groups are very linkage-intensive, and need considerable interaction between firms to reach "best practice" technical efficiency. We divide them into three sub-groups. MT1, automotive products, are of particular export interest to newly industrialising countries, particularly in East Asia and Latin America. MT2, process industries – mainly chemicals and basic metals – are different in their technological features from MT3, engineering products. Process industries have stable and undifferentiated products, often with large-scale facilities and considerable technological effort in improving equipment and optimising complex processes. Engineering industries emphasise product design and

development. Many have mass assembly or production plants and extensive supplier networks (SMEs are often important here). Barriers to entry tend to be high. The relocation of labour-intensive processes to low wage areas occurs but is not widespread: products are heavy and need advanced capabilities to reach world standards.

- **High-technology (HT) products** have advanced and fast-changing technologies, with high R&D investments and prime emphasis on product design. The most advanced technologies require sophisticated technology infrastructures, high levels of specialised technical skills and close interactions between firms, and between firms and universities or research institutions. However, some products like electronics have labour-intensive final assembly, and their high value-to-weight ratios make it economical to place this stage in low-wage areas. These products lead in new internationally integrated production systems where different processes are separated and located by MNCs according to fine differences in production costs. We separate HT1, electronic and electrical products from HT2, other high-tech products. Apart from electronics, other high-technology products (generating equipment, aircraft, precision instruments and pharmaceuticals) remain rooted in economies with high levels of skills, technology and supplier networks. Their comparative advantage continues to be ruled by the usual technological factors.

Services trade

Analysis of service exports relies on the IMF Balance of Payments Manual (BPM6) classification of disaggregated data on credit accounts of services at 1-digit level (https://data.imf.org). The BPM6 provides credit, debit and net accounts for services over 2010–20. The coverage of trade in services data is still very limited and often unbalanced. Services, in contrast to goods, are characterised by several features, such as intangibility and non- storability, which complicate the collection of accurate international trade in services statistics (50). In the spirit of (18–20) the combined goods and services dataset of world trade has been referred to as the universal matrix of world trade. Table 2 gives our classification of services into "traditional" versus "modern".

1-digit of service exports codes, IMF Balance of Payments Manual 6 — Table A2

BPM6 code	Definition	Label
BXS_BP6	Services, Credit	Total service exports
BXSM_BP6	Services, Manufacturing services on physical inputs owned by others, Credit	Modern
BXSTR_BP6	Services, Transport, Credit	Traditional
BXSTV_BP6	Services, Travel, Credit	Traditional
BXSOCN_BP6	Services, Construction, Credit	Traditional
BXSOIN_BP6	Services, Insurance and pension services, Credit	Traditional
BXSOFI_BP6	Services, Financial services, Credit	Modern
BXSORL_BP6	Services, Charges for the use of intellectual property n.i.e., Credit	Modern
BXSOTCM_BP6	Services, Telecommunications, computer, and information services, Credit	Modern
BXSOOB_BP6	Services, Other Business Services, Credit	Modern
BXSOPCR_BP6	Services, Personal, cultural, and recreational services, Credit	Traditional
BXSOGGS_BP6	Services, Government goods and services n.i.e., Credit	Traditional

Source: IMF.

Country coverage

Country coverage — Table A3

Advanced economies		Emerging and developing economies	
Australia	New Zealand	Albania	Moldova
Austria	Norway	Argentina	Mongolia
Belgium	Portugal	Azerbaijan	Montenegro
Canada	Singapore	Bangladesh	Mozambique
Croatia	Slovakia	Belarus	Nigeria
Cyprus	Slovenia	Brazil	North Macedonia
Czechia	Spain	Bulgaria	Pakistan
Denmark	Sweden	Cambodia	Peru
Estonia	Switzerland	Chile	Philippines
Finland	United Kingdom	China	Poland
France	United States	Colombia	Romania
Germany		Ecuador	Russia
Greece		Egypt	Serbia
Hong Kong SAR		Georgia	South Africa
Iceland		Ghana	Sri Lanka
Ireland		Hungary	Sudan
Israel		India	Thailand
Italy		Indonesia	Tunisia
Japan		Iran	Türkiye
Korea		Jamaica	Uganda
Latvia		Jordan	Ukraine
Lithuania		Kazakhstan	Uruguay
Luxembourg		Malaysia	Venezuela
Malta		Mauritius	Vietnam
Netherlands		Mexico	Zimbabwe

The country groups follow the classification from the IMF *World Economic Outlook*.

Source: IMF, *World Economic Outlook*.

Appendix B: pairwise correlations

Pairwise correlations

Table B1

	Investment in artificial intelligence[1]	Investment in AI for real estate / insurtech[1]	Investment in AI for fintech[1]	Investment in AI for retail[1]	Investment in AI for network technology[1]	Investment in AI for robots[1]	Trade openness	Share of government consumption in real GDP at current PPPs	UN education index	Domestic banking credit to private sector as a share of GDP	Foreign direct investment, net inflows (% of GDP)
Investment in artificial intelligence[1]	1										
Investment in AI for real estate / insurtech[1]	0.48	1									
Investment in AI for fintech[1]	0.82	0.44	1								
Investment in AI for retail[1]	0.58	0.61	0.58	1							
Investment in AI for network technology[1]	0.52	0.52	0.44	0.58	1						
Investment in AI for robots[1]	0.62	0.55	0.52	0.63	0.64	1					
Trade openness	0.09	–0.10	0.08	–0.08	–0.11	–0.07	1				
Share of government consumption in real GDP at current PPPs	–0.06	–0.05	0.02	–0.08	–0.07	–0.01	0.12	1			
UN education index	0.32	0.12	0.28	0.23	0.13	0.31	0.27	0.41	1		
Domestic banking credit to private sector as a share of GDP	0.21	0.20	0.10	0.09	0.13	0.19	0.29	–0.07	0.45	1	
Foreign direct investment, net inflows (% of GDP)	0.00	–0.07	–0.001	–0.03	–0.07	–0.08	0.44	–0.06	0.04	0.30	1

[1] Five-year rolling sum of investments in the specific AI vertical divided by population in each given year. Figures are expressed in USD per capita.

Sources: IMF; UNU-WIDER, *World Income Inequality Database (WIID)*; AI investment data; United Nations; World Bank; authors' calculations.

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