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The Impact of Artificial Intelligence on Productivity and Employment – How Can We Assess It and What Can We Observe?

Technological optimists have been predicting the artificial intelligence (AI) revolution since the beginning of the past decade. This expectation contrasts with low productivity growth in many countries. The commercial release of ChatGPT in late 2022 has lead to rising expectations about a dramatic shift at least equivalent to the one associated with the commercial introduction of the Internet. But what is AI from an economic point of view? How can we observe the diffusion of AI in the economy and assess its effects in order to the draw conclusions for economic policy?

This article starts from a bird's eye view, detailing how automation and AI are modelled in economic theory and how their productivity and employment effects are currently measured. In the framework of national accounting, many AI systems can be considered bundles of different categories of investment. This makes them hard to measure. Much preliminary evidence on economic effects of the diffusion of AI is thus based on measures of AI exposure or AI skill demand rather than its use. First evidence suggests that AI-using firms may experience positive productivity and non-negative employment effects while aggregate effects are still too small to detect.

What is artificial intelligence?

Among the many definitions of AI, we focus on some taken from economic research. In the introduction to *The Economics of Artificial Intelligence: An Agenda*, the editors Agrawal et al. (2019, 3) write:

> The Oxford English Dictionary defines artificial intelligence as 'the theory and development of computer systems able to perform tasks normally requiring human intelligence.' This definition is both broad and fluid. There is an old joke among computer scientists that artificial intelligence defines what machines cannot yet do.

According to this logic, AI would be a concept with a concrete meaning that varies over time, since it once included, for example, early chess computers, but does not include them anymore because beating professional chess players is no longer an insurmountable challenge for computers. Still, earlier waves of computer technology that diffused within the economy were not commonly associated with the term "artificial intelligence". With regard to commercially viable applications, the term has been mainly employed since around 2012 for machine learning (a set of methods from computations statistics) as a prediction technology (Agrawal et al., 2019). The OECD (2019, 15) defines an AI system as a "machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments.... AI systems are designed to operate with varying levels of autonomy".[1]

The AI Act of the EU, which was approved by the Council of the EU's Committee of Permanent Representatives on 2 February this year, is an important policy framework for the use of AI in the economy. It defines AI systems in a similar way. Simpler software systems that are "based on the rules defined solely by natural persons to automatically execute operations" (Proposal for a Regulation 2021/0106 (COD), 2024, paragraph 6)[2] are not considered AI systems. AI systems are designed to operate with varying levels of autonomy, meaning that they have some degree of independence of actions from human involvement and

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1 See Barrufaldi et al. (2020, 11).

2 The version of 21.1.2024 has been released by individual parliament members and by journalists and is made available online by the non-profit Future of Life Institute.

of capabilities to operate without human intervention. The adaptiveness that an AI system can exhibit after deployment refers to self-learning capabilities, allowing the system to change while operating to attain the explicit or implicit objectives specified for it (Proposal for a Regulation 2021/0106 (COD), 2024, paragraph 6). In view of relating the definition of AI systems in a legal context to an economic context (such as, for example, the set of definitions underlying the international System of National Accounts, SNA), the following statement is worth considering:

> AI systems can be used on a stand-alone basis or as a component of a product, irrespective of whether the system is physically integrated into the product (embedded) or serve the functionality of the product without being integrated therein (non-embedded) (Proposal for a Regulation 2021/0106 (COD), 2024, paragraph 6).

AI as a factor of production

The perspective taken here focuses in a relatively abstract way on the modelling of AI as an input to a firm-level or macroeconomic production function. This does not consider the role AI can play in concrete economic prediction and decision-making tasks.

In a highly stylised way, Growiec (2022) describes four stages of substitution of labour by capital. In the first, pre-AI, phase of mechanisation, capital is only capable of substituting for physical human labour. The second phase is automation (which may or may not be counted as using AI, depending on the definition of AI), with software substitution for some cognitive human labour, in particular in factory automation through robotics. The third phase represents the use of machine learning, mainly for prediction, which replaces cognitive human labour rather than automation, since software can now be self-improving. In the future, some researchers envision economies will enter a fourth phase, the phase of superintelligence, in which computers will be capable of a general intelligence that exceeds human intelligence in all respects. All physical tasks then become programmable and all human cognitive labour can be substituted by artificial intelligence. This state is also called singularity.

All macroeconomic models about automation and about AI have at the core some simple production theoretic models that make assumptions about functions or tasks that technology can perform. If the technology performs the same function as some category of human labour, both are perfect substitutes. If it does not perform the same function, both are imperfect substitutes, unless their functions themselves can be substituted by one another in the production process. Macroeconomic models usually defined AI based on simple assumptions of substitution. Their complexity then comes from how these substitution properties interact with other features of the model. Whether technology eventually substitutes for human labour depends on relative prices and other firm and market conditions.

Different ways have been proposed to model substitution between technology and labour. Sometimes, the technology input is called “automation capital”, whereas the terminology “AI capital” or “AI systems” as a category of capital is not used. This may reflect the uncertainty about the empirical counterpart of what we conceptualise as AI in macroeconomic models. The prototypical production-theoretic conceptualisations are the following:

In one variant, within a macroeconomic production function with capital and labour as production factors, automation capital has a substitution parameter with labour that is different from its substitution parameter with other capital. Some models assume substitution between automation capital is perfect (Berg et al., 2018; Gasteiger and Prettner, 2022).

A second variant represents macroeconomic production technology as a set of tasks. Progress in automation and artificial intelligence increases the fraction of tasks that can be performed by machines instead of humans (Aghion et al., 2019).

In a third variant, this set of tasks itself expands and there is a task-specific productivity (Acemoglu and Restrepo, 2018).

If model implications are to be tested, empirical measures that match the way automation or AI is conceptualised have to be found. In the following, we give a brief overview of empirical measurements and results. The aim is to show the challenges associated with measuring the diffusion of AI systems throughout the economy and with observing its effects on productivity and labour substitution.

The public debate often focuses on the job losses resulting from automation. Empirical evidence to date, however, does not point to any aggregate job losses (Autor, 2015). Productivity effects from the diffusion of computer technology have been visible, in particular between 1995 and 2005 (Cardona et al., 2013). They are high when considering the small share of ICT capital in total capital but not spectacular when considering overall economic growth in rich economies in the 20th century. Whether the current wave of technological progress based on machine learning technologies has different effects is yet to be seen.

Investment in new and better capital goods is expected to have positive aggregate effects on labour productivity in the medium run. Without these effects, there would be no plausible reason for large-scale capital investment in economies. In the short run, the diffusion of new technologies may be initially too small, and adaptation costs may be too high to observe positive aggregate productivity effects.

Different kinds of negative employment effects of automation and AI are possible for individual firms: investment in automation or AI may directly substitute workers. Also, firms that lag behind in investment in automation and AI may lose market shares and thus reduce employment. On the other hand, firms that are leaders in investment in automation and AI may capture market shares through cost reduction or product innovation and increase employment. Moreover, investment in automation and AI may increase productivity and thus real incomes, which may positively affect product demand and employment. The sectoral and aggregate employment effects depend on the price elasticity of product demand.

Measuring automation and AI technologies

Assessing the employment and productivity effects of the diffusion of AI systems requires measuring their use in firms empirically. In the system of national accounting, immaterial inputs and those with rapid quality change over time are much more difficult to measure than material inputs and those with moderate quality change. Capital inputs are those non-human inputs that last longer than a year in the production process. Material capital inputs include:

- building and structures
- vehicles
- non-IT machinery and equipment and weapon systems
- ICT equipment (computer hardware and communications equipment).

These categories are all included in the current international standards of national accounting (SNA 2008). Immaterial capital inputs include:

- computerised information: software and databases
- innovative property: research and development (R&D), mineral exploration, artistic originals, design
- economic competencies: firm-specific training, market research and branding, business process re-engineering.

Software has been included since SNA 1993, and measurement was implemented in developed countries by 2000. Issues with quality measurement continue to be substantial. In principle, since SNA 1993 databases were also to be measured, but this has considerable intricacies both at the conceptual and at the practical level, thus implementation is uneven. R&D has been thought of as an investment only since SNA 2008. Previously, it was considered an intermediate expenditure on the same account as materials or energy. R&D investment is measured mostly by expenditure on R&D personnel.

In the European Union, the inclusion of R&D investment in national accounts began in 2014. Economic competencies are to date not considered investment in national accounting. Measurements of the amount of investment in this category have been created in research projects such as the INTAN-Invest Database (Corrado et al., 2021). Regarding the measurement of AI in national accounts, Corrado et al. (2021, 473) "think of AI as using a combination of tangible assets (hardware) with measured intangibles (software) and unmeasured intangibles (databases)".

For research projects in economics, the most widely used measure of automation is the number or the capital value of industrial robots. The availability of data on industrial robots worldwide in the database of the International Federation of Robotics (IFR) has sparked a lot of empirical research in recent years (Jurkat et al., 2022). An industrial robot is an "automatically controlled, reprogrammable multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or fixed to a mobile platform for use in automation applications in an industrial environment" (ISO standard 8373:2012 (§ 2.9) reported in Jurkat et al., 2022, 671). In national accounting, industrial robots and similar, less well-measured automation technologies, are part of non-IT machinery. They may be bundled with software components, which are in turn part of computerised information. Based on investment data for nine manufacturing industries in ten countries for the period 1993-2007, we find that quality-adjusted robot investment has an average share be-low 1% of total investment.[3] Automation capital measured as robot capital represents thus a very small fraction of total investment. Only few studies are capable of observing a broader set of automation machinery and equipment (Aghion et al., 2023).

Over time, progress in industrial robotics leads to the emergence of robots with an increasing degree of autonomy. In particular, the algorithms controlling them have been moving from deterministic to probabilistic algorithms (IFR, 2022), which according to the definitions used by OECD and EU can be seen as the threshold for belonging to AI systems rather than non-AI automation technology. Research with available data since the early 1990s will, however, mostly likely capture the effects of the pre-AI era.

As with computer hardware, and more importantly computer software, amounts of investment into industrial robots need to be quality adjusted when added up to a capital stock. While the IFR provides some information on how to quality adjust robot prices, measurement error is likely to remain substantial.

In order to capture a broader set of automation technologies, some studies link information on automation-related patents to information on workers' tasks or on industries for which the content of these patents is particularly relevant (see survey by Aghion et al., 2023).

To date, only few data directly and comprehensively measure the use of AI systems in firms in a way that distinguishes them from pre-AI software. As with standard ICT investment, binary measures of adoption of AI technologies may be easier to collect from firms and may yield a more nuanced picture of the technological level of the investment than monetary measures of hardware and software investment in line with national accounting. In one of the few studies with direct and comprehensive measures of AI use within firms, Czarnitzki et al. (2023) can observe the use of four broad AI methods in five different areas of the firm's activity. Data from 2018 come from the German part of the European Community Innovation Survey. Out of the nearly 6,000 firms observed in the sample, 7% report any kind of use of AI methods. Most current economic research until now uses narrower AI measures related only to certain areas of the firm's activity or indirect measures of AI diffusion based on bibliographic data from scientific publications, patent data (Barrufaldi et al., 2020) and job-related descriptions, for example, in job advertisements (Acemoglu et al., 2022).

Evidence on productivity and labour market effects of automation and AI

Effects of industrial robot use on labour productivity and total factor productivity (TFP) at the industry level appear to be mostly positive (Graetz and Michaels, 2018; Jungmittag and Pesole, 2019; Kromann et al., 2019) and in some cases surprisingly large given the small share of robot equipment in overall capital.

A survey by Aghion et al. (2023) finds mixed effects of industrial robot use on employment at the country or industry level. In most empirical research, robot use is measured at the industry level or extrapolated to the local level using industry-level data. Depending on the country observed and the research design, one robot is found to replace between 0 and 10 workers. Studies using text analysis or patent data find similarly mixed results. Firm-level studies find positive employment effects of industrial robot use. Automating firms have between 2% and 10% higher employment. The positive elasticity of employment to robot investment lies between 0.2% and 2%. Aghion et al. (2023) argue that industry-level evidence shows only the net result of effects in automating and non-automating firms. Firm-level evidence suggests that negative employment effects may be experienced by non-automating firms, which are less competitive.

In a meta-analysis of 53 studies, Jurkat et al. (2023) find an overall wage effect of industrial robot use that is close to zero. Effects tend to be more negative in estimations for manufacturing industries as well as at the country level compared to more disaggregated levels.

In their study applying data on the use of AI methods in firms, drawing on one of the most comprehensive measurements currently available, Czarnitzki et al. (2023) find a positive and significant association between AI use and firm productivity based on a variety of different measures. Surveying a small number of studies published between 2017 and 2021, Calvino and Fontanelli (2023) find the evidence on AI and firm productivity inconclusive. From their own analysis based on harmonised microdata from the OECD diffuse project, they find productivity advantages of AI users, which seem to be related to complementary assets such as ICT skills and digital infrastructure.

Identifying AI-exposed establishments through online vacancies, Acemoglu et al. (2022) find that they in-

3 Own calculations using data from the International Federation of Robotics (IFR) and EUKLEMS from ongoing research with Anne Jurkat and Julian Salg.

crease hiring in AI-related jobs. At the same time, firms decrease hiring in jobs not directly related to AI and change the skills demanded for these jobs. According to their analysis, aggregate effects on employment and wages are currently too small to be detectable. Babina et al. (2024) find evidence for higher employment growth in AI investing firms coming through the channel of product innovation.

Overall, both research on robot and AI diffusion point to positive productivity and employment effects at the firm level, while employment effects at the industry-level are less clear-cut. It may also be too early to observe aggregate productivity effects of AI.

Conclusion

While policies such as the EU AI Act, which aims at establishing a regulation for AI applications that may represent high risks and intransparencies for citizens, begin to develop a clear definition of the technologies to which this concept refers, AI as an economic input is hard to measure. This becomes evident when looking at the diffusion of those automation technologies that emerged prior to current AI but continue to develop with enhanced software capabilities. The most commonly used empirical measure of these automation technologies is industrial robot use, quantified as the number of robots or real value of robot capital stock. This measure may not fully capture the value of software and databases created and used in association with the robots.

AI systems more generally may, in terms of categories of national accounting, be considered bundles of computer hardware, software and database investment, in some cases also associated with investment in machinery that is not counted as computer hardware or investment in R&D. This implies that the overall economic value of AI systems is already to a large extent included in gross domestic product, with the exception of the value of databases, which is poorly measured. But national accounts and similarly built databases currently do not allow for the identification of AI systems as a separate category. Therefore, firm und industry-level research concerning the productivity effects of AI currently relies on other indicators. Some of them, such as data from job advertisements, do not allow the direct observation of the level of AI use in firms but rather measure AI exposure. Given the high importance of observing the future opportunities and risks associated with the diffusion of AI, the further development of firm-level measurement seems warranted.

To date, there is no evidence of massive overall job losses caused by AI that some observers tend to anticipate based on studies (such as, e.g. Frey and Osborne, 2017) that assess only the technological substitution potential of current jobs. It remains to be seen how far the previous experience of computer diffusion since the 1970s, which changed job tasks and affected various skill groups differently, but did not lead to higher aggregate unemployment, will be repeated with the further diffusion of AI technologies.

While there seems to be a large potential for AI productivity effects that lead some observers to see the possibility of a “singularity” of explosive economic growth in the more distant future, aggregate productivity effects may still take some years to be measurable.

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