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Macroeconomic Productivity Effects of Artificial Intelligence

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Abstract: Some observers expect that the current wave of new tools based on artificial intelligence (AI) models, such as the large language models, will have strong effects on labor productivity. I present definitions and classifications that help understanding AI as an economic input. I then review theoretical and empirical arguments about macroeconomic productivity effects of AI and conclude that research has so far found no indication that productivity effects of the diffusion of AI are likely to be higher than those associated with the internet boom around the year 2000. While considerable uncertainty around future effects remains, a recent review and calibration exercise by Acemoglu, D. (2024. *The Simple Macroeconomics of AI.* Cambridge, MA: National Bureau of Economic Research, Working Paper 32487) suggests that the effects might be a lot lower.

Keywords: artificial intelligence; productivity; economic growth

JEL Classification: O47

1 Approaching the Economic Singularity?

Automation has been inspiring science-fiction-like scenarios of exploding economic growth and massive redundancy of work at least since the beginning of the computing era in the 1940s and in a broader sense already since the beginning of the industrial revolution. The so-called singularity hypothesis discussed by computer scientists and engineers sees a potential of generating widespread prosperity more and more effortlessly, while human labor and intelligence would be becoming increasingly superfluous. The formulation of the concepts of singularity and super intelligence has been ascribed to mathematician John von Neumann. There are, however, few written traces for this claim (Nordhaus 2021). In purely technical terms, the cost of computing power has declined by a factor of two-digit millions since the 1960s. The current wave of development in artificial intelligence (AI) has

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long been expected as the step where computers would come closer to the working capacity of the human brain, although speed of computers cannot be directly translated into human intelligence.

Nordhaus' (2021) arguments why an economic singularity does not seem anywhere near do not depend on any specific properties of the current wave of AI. A productivity singularity that would rely on productivity increase in immaterial information goods depends on the role of these goods in supply and demand. In production of supply, information goods would need to be sufficiently good substitutes for physical inputs (human labor, natural resources). In demand, the price elasticity for information-intensive goods would need to be higher than one. An elasticity higher than one implies that the share of spending on these goods increases when prices decrease, because the higher quantity demanded outweighs the lower spending per unit. With American data for 1929–2012, Nordhaus does not see any plausible indication that the economy might be approaching a singularity in any foreseeable future. I think the arguments would not change with data from the most recent decade. With the need to counteract climate change, scarcity of physical inputs (including energy input for the use of AI) may be even a stronger restriction than in earlier times. Technological optimists anticipate that a revolution in the use of solar energy may free up a large potential for the economy (The Economist 2024). Though I am not in the position to take any stance on the likelihood of this scenario here, I guess that the potential of this scenario for maintaining and increasing worldwide prosperity is higher than the potential of the current wave of AI.

In the early 2010s, economists Eric Brynjolffson and Robert J. Gordon held a controversy on the question whether most of the productivity effects of the digital revolution have already been realized in rich countries or are still to come (see, i.a., Gordon 2012; Brynjolfsson and McAfee 2014). While Gordon thinks that the satisfaction of human needs advanced by the industrial revolution and its aftermath during the period 1870–1970 has mostly reached its limits in rich countries, Brynjolfsson argues that ever cheaper computing power will fuel innovation in ways that are hard to overestimate. Referring to an ancient legend where someone demands for a doubling of the rice grains per field of the chessboard, he considered that the years to come would be "the second half of the chessboard", where exponentially improving computing power reaches levels of performance beyond current imagination.

2 What is Artificial Intelligence?

Among the many definitions of AI, one commented definition that is useful for considering its economic impact is given by Agrawal, Gans, and Goldfarb (2019, p. 3):

"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, the concrete meaning of the concept of AI would be varying over time. 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 computational statistics) as a prediction technology (Agrawal, Gans, and Goldfarb 2019). The OECD (2019, p. 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 …".

The recent AI Act of the EU considers that AI does not "cover systems that are based on the rules defined solely by natural persons to automatically execute operations" (Official Journal of the European Union 2024, p. 4). AI systems "are designed to operate with varying levels of autonomy" (ibd.), meaning that they have some degree of independence of actions from human involvement. 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 (ibd.). The following description focuses on AI as an economic input: "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 serves the functionality of the product without being integrated therein (non-embedded)" (ibd.).

3 Measurement of Productivity Effects of AI

3.1 Defining AI as an Economic Input

If we want to understand the effect of AI on economic growth, we need to define and to measure it as an element of an economic production technology. Recent work has defined automation capital or AI as a separate capital good. Alternatively, it can be considered as an area of technological knowledge that enables innovation in capital goods. This innovation expands the range of tasks in production that do not need to be performed by humans (see Saam 2024). Capital inputs are 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, and
- 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:
- computerized information: software and databases,
- innovative property: research and development (R&D), mineral exploration, artistic originals, design, and
- economic competencies: firm-specific training, market research and branding, business process re-engineering.

Software has been included since the SNA revision of 1993, and most developed countries implemented measurement by 2000. Issues with quality measurement continue to be substantial. R&D has been conceived as an investment only since SNA 2008. Previously, it had been considered an intermediate expenditure on products lasting less than a year. Economic competencies are currently only measured outside official national accounting. AI systems used in firms typically contain elements of hardware, software and databases. R&D capital and economic competencies may also contribute to their function as an input within firms (Corrado, Haskel, and Jona-Lasinio 2021). Their overall economic value is mostly included in current national accounting, but at the macroeconomic level, they are not distinguishable as a separate category in the accounts.

3.2 Measuring Diffusion of AI

Data collection for research purposes on use of AI systems in firms is also challenging. Challenges include the reluctance of firms to share information on monetary investments and the difficulty of distinguishing AI from pre-AI software. In one of the few studies with direct and comprehensive measures of AI use within firms, Czarnitzki, Fernández, and Rammer (2023) are able to 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, seven percent report using AI methods in some way. 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 and patent data (Barrufaldi et al. 2020). Current research assessing the overall productivity potential of AI relies mostly on job task descriptions. Data are gained from matching occupations of existing jobs with task descriptions or from job advertisements that refer to AI competencies. AI exposure of an industry can then be measured by the extent of tasks that could be substituted by AI, by the demand for AI skills or by the number of AI patents that relate to technologies used in the industry (Saam 2024). AI exposure as such does not contain information on the actual degree of usage of AI, but rather on availability or demand for technology or skills that could be used to implement AI in the industry. When the goal is the assessment of the upper bound of industry-level and macroeconomic productivity growth resulting from the diffusion of AI, observing AI exposure instead of actual AI usage may not be an obstacle.

4 Macroeconomic Productivity Effects of the Diffusion of AI: Likely to be Visible, but Not Large

Daron Acemoglu and his co-authors have developed a theoretical framework in which automation expands the set of tasks that capital goods can perform at the place of humans. In this setting, AI can affect macroeconomic labor productivity via four channels: (1) increasing the range of tasks that can be automated, (2) increasing marginal productivity of tasks performed by human labor, (3) reducing the cost of automation of tasks, (4) creating new tasks or products.

AI is the latest wave of technology that may affect productivity via these channels. Acemoglu (2024) matches the modeling approach with first empirical evidence on productivity effects of AI and derives approximations of their size based on a growth accounting approach. Growth accounting decomposes GDP growth into contributions of different production factors and technological change based on the assumptions of constant returns to scale and competitive factor markets.

In calibrating the model, Acemoglu distinguishes between tasks that are easy for current AI and tasks that might be feasible but are hard for current AI. Moreover, he incorporates the effect of additional investment triggered by the diffusion of AI. Interestingly, he also takes into the account the effect of “new bad tasks”, which increase firm revenues but reduce consumer utility by manipulating consumers or encouraging addictive behavior. While much public interest currently lies on generative AI used in large language models (LLM), Acemoglu considers his estimate to apply to all economic benefits of AI, including also computer vision, which may have further new applications for example in robotics.

Acemoglu’s (2024) main finding is that AI can be expected to increase US GDP by one percent in total over 10 years. This corresponds to an additional annual growth of 0.1 percentage points per year. The lower bound of the estimate is 0.93 percent over

10 years, the upper bound including an investment boom is 1.56 percent. When we compare these effects of AI to the productivity effects that the internet revolution around the year 2000 has in the US, these numbers look rather modest. Cardona, Kretschmer, and Strobel (2013) survey different studies covering the years 1990–2005 and report a combined contribution of total factor productivity growth in the IT sector and IT investment to labor productivity growth between 36 and 73 percent. Assuming a 1 percent GDP growth in total and a constant work force, this would correspond to 0.36 to 0.73 percentage points of GDP growth per year resulting from digitalization. If GDP growth was higher, the effect would be even larger. While AI is currently transforming production and consumption and can be expected to do so for a while, the fundamental revolution heralded by some news media and business reports seems unlikely, at least when we look at GDP. If we take into account that the US has been leading on the internet revolution around the year 2000 and continues to play a leading role in AI today, GDP effects in other countries could be even smaller. Still, the argument is based on very first pieces of evidence on AI exposure and diffusion of AI. The uncertainty attached to it is not negligible. With regard to distributional effects, Acemoglu's exercise suggests that the current wave of AI may moderately increase income inequality.

As a research infrastructure, my own institution, the ZBW – Leibniz Information Centre for Economics, is working on guiding and supporting researchers in applying AI tools to search and information extraction of academic papers. In the way I currently perceive this task, I concur with Acemoglu's (2024) final appreciation of the state of LLMs: There "are indeed much bigger gains to be had from generative AI, (…) but these gains will remain elusive unless there is a fundamental reorientation of the industry (…) in order to focus on reliable information that can increase the marginal productivity of different kinds of workers, rather than prioritizing the development of general human-like conversational tools. (…) To put it simply, it remains an open question whether we need foundation models (…) that can engage in human-like conversations and write Shakespearean sonnets if what we want is reliable information useful for educators, healthcare professionals, electricians, plumbers and other craft workers" (Acemoglu 2024, p. 45).

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