The ICT revolution and the future of innovation and productivity

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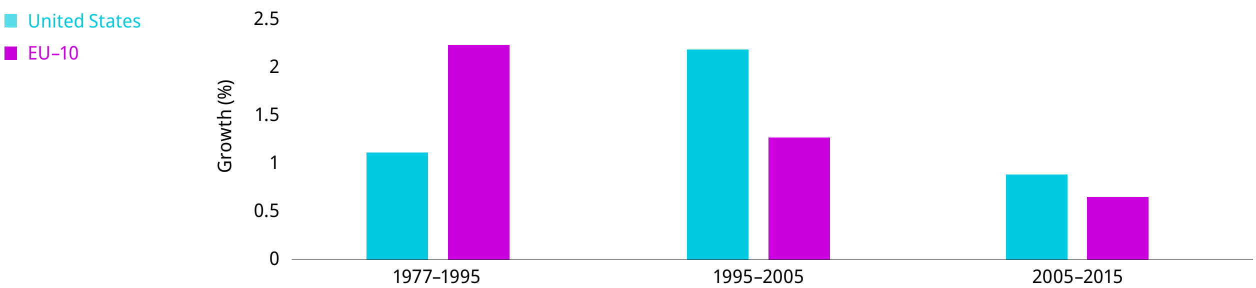
Introduction

In the years following the Second World War, multiple countries witnessed phenomenal productivity growth. This economic expansion came with high employment rates and was peculiar to the United States of America (US), the Soviet Union, Western Europe and East Asian countries. It lasted until the 1970s, when an economic recession in the Western world occasioned high inflation and unemployment.

In the 1970s, there was a new industrial revolution based on information and communication technologies (ICT). It signaled the beginning of a new era, when the rise and systematic adoption of electronics, telecommunications and computers disrupted business and economic models by providing greater efficiency gains in the production process, as well as novel possibilities and modes of communication. Continuous advances in ICT technologies have led to a new digital reality, where new sectors, products and services have been developed in a rapid digitalization of the world economy, with high-level automation a popular industrial and business practice.

Despite large-scale ICT deployment, it has not proved possible to capture substantial long-term benefits in productivity statistics. This is perfectly reflected in the famous quote by Nobel Laureate, Robert Solow: “You can see the computer age everywhere but in the productivity statistics.”[1] In fact, some productivity growth benefits have been observed, but they took time to arrive, were US-specific and not long-lasting. The US economy experienced a productivity growth revival between 1995 and 2005 not observed in other major economies, for instance, those in Europe (Figure 3.1).

Figure 3.1 Labor productivity growth rates for the US and European Union-10



Source: Gordon and Sayed (2020).

A study by Gordon and Sayed found that the US productivity revival was driven by intense investments in ICT, which led to additional productivity growth in (i) ICT-intensive service-producing industries and (ii) the electrical machinery industry producing computer hardware.

In contrast, European countries did not invest heavily in computer hardware, and for them ICT-producing industries have had far less importance.[2] As a consequence, Europe failed to reap the productivity benefits of the ICT revolution.

During the years of substantial productivity growth, US ICT-intensive industries experienced a revival in productivity growth of roughly 2 percentage points, whereas the productivity growth of non-ICT intensive industries remained at the same low level as before.[3] In addition to heavy ICT investments, structural market changes, including the emergence of more flexible labor markets, as well as increases in dynamic competition and reallocation effects, also helped the US productivity revival.[4]

Over the last decade, artificial intelligence (AI) has come to be regarded as the next important step in the ICT revolution. AI can be defined as the use of machines and software developed with specific techniques and approaches for a given set of human-defined objectives, generating outputs such as content, predictions, recommendations or decisions influencing the environments with which they interact. The techniques and approaches most frequently used in AI are machine learning (supervised, reinforcement and unsupervised learning); logic- and knowledge-based approaches (e.g., inductive logic programming with the use of deductive engines); statistical approaches (e.g., Bayesian estimation); and search and optimization methods.

A key characteristic of AI systems is their incorporation of a "learning-by-doing" function by which they become ever more efficient through the execution of tasks and experimentation with relevant training data. As a result, AI systems are able, for example, to substantially improve the efficiency of production processes for goods and services, when "fed" good quality, relevant (training) data.

AI is considered a general-purpose technology (like the steam engine, electricity and computers before it) with a wide variety of applications in many industries and sectors. The fastest growing type of AI technology is related to deep learning applications. AI-related patent filings have particularly grown in the field of computer vision, including character recognition, biometrics, scene understanding, image and video segmentation, object tracking and augmented reality (see GII 2022 Expert Contribution from Peters and Trunschke).[5]

There have been tremendous improvements in the ability of AI systems to perform a given task. As an example, in recent years, AI systems have managed to outperform human image recognition in the ImageNet Large Scale Visual Recognition Challenge.[6] This challenge evaluates an algorithm's capabilities in regard to object detection and image classification at a large scale. For any given word, ImageNet contains several hundred images. In the annual ImageNet contest, several research groups compete to get their AI computers to recognize and label images automatically. Humans on average label an image correctly 95 percent of the time. The winning AI system in 2010 scored 72 percent, but over the intervening years the error rate fell sharply, until in 2015 machines managed to achieve a 96 percent accuracy, and in so doing reduced the error rate to below the human average for the first time.

Another indicative example is the General Language Understanding Evaluation (GLUE) benchmark. GLUE tests single AI systems on nine distinct tasks in an attempt to measure the general natural language understanding of AI systems compared to human understanding. Tremendous progress has been made in the accuracy of these systems in just the last few years. Although the benchmark was released as recently as May 2018, AI systems had already surpassed non-expert human performance by June 2019, and have continued to improve since.

AI systems have also improved markedly in other tasks such as speech recognition, (visual and verbal) question answering, translation from one language into another, language understanding and inference, text summarization, sentiment analysis and so on.

Despite the tremendous improvements which have seen AI machines achieve an efficiency level equal to, or even greater than, that of a human when performing a specific cognitive task, their contribution to the production process is not captured in the aggregate productivity statistics. Since 2005, US labor productivity has grown at an average annual rate of just 1.3 percent. The sluggish rate of growth observed since 2010 is even more striking – labor productivity grew by just 0.8 percent from 2010 to 2018.

The remainder of this paper is devoted to explaining the AI productivity paradox, and, in doing so, providing some policy recommendations on how to increase innovation and knowledge spillovers in order to revive productivity growth.

Explaining the AI paradox: the productivity J-curve

The productivity J-curve describes the historical pattern of initially slow productivity growth after the introduction of a breakthrough technology followed years later by a steep take-off. As an example, after the introduction of electricity to American factories, productivity remained stagnant for over two decades. It was only once managers reinvented production lines so they could use distributed machinery – a technique made possible by electricity – that (belatedly) productivity surged. And it is not only electricity that required such a reinvention of work. A study by Brynjolfsson and colleagues finds that complementary investments in intangible capital are almost always needed before big technology breakthroughs as diverse as the steam engine or computers ultimately boost productivity (see GII 2022 Expert Contribution from Peters and Trunschke).[7] Firms need to rethink their business models; managers need to develop expertise for the Digital Age; workers need to be retrained so they can interact with new technologies; complementary web applications and software need to be designed. Consequently, over time, the impact made by new, general-purpose technologies on growth has two distinct phases. There is an initial phase, when intangible capital is created and accumulates, after which there is a productivity boom phase (see GII 2022 Expert Contribution from van Ark and Fleming).

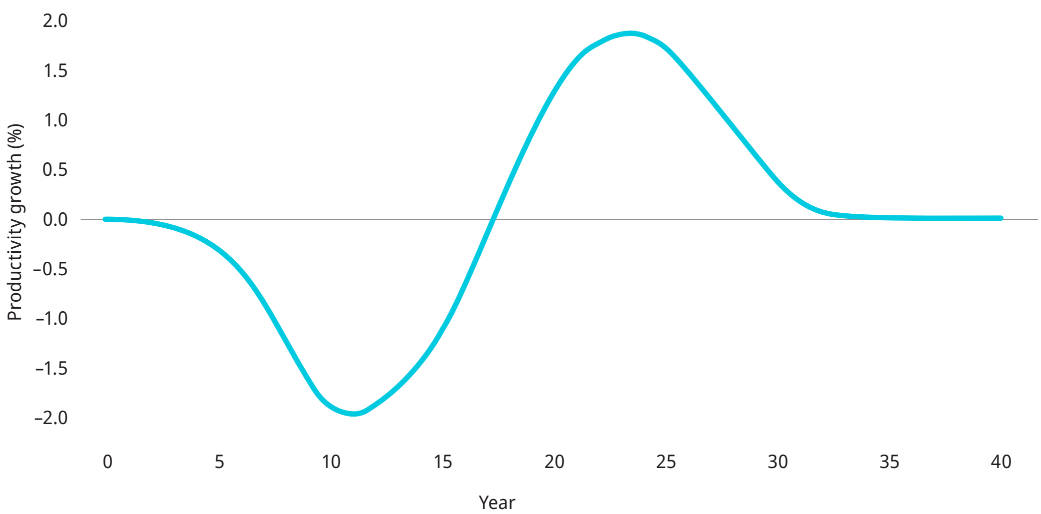
In the case of AI, we can reasonably expect the productivity J-curve to be valid. AI requires that complementary innovations take place in order to pay off in aggregate statistics. Hiring and training highly specialized AI talent and adopting a more collaborative model of production that includes the active involvement of humans and machines can help arrive at the productivity boom phase.

However, we cannot ignore the fact that complementary investments are based on intangible capital and that this is not well captured by productivity statistics. The chief economist at Google gives an illustration as to why intangible capital is so difficult to measure:

> in 2000, there were 80 billion photos produced. We know that because there were only three companies that produced film. And fast-forward to 2015, there are about 1.6 trillion photos produced. Back in 2000, photos cost about 50 cents apiece. Now they cost zero apiece essentially. So, any ordinary person would say, wow, what a fantastic increase in productivity, because we've got a huge amount of more output and we've got a much, much lower cost. But if we go look at that from the GDP lens, it doesn't show up in GDP for the most part because those photos are typically traded among friends and put in albums and things like that. They're not sold on the market. GDP is the market value of transactions out there, and anything that's not sold or has a zero price isn't going to show up in GDP.[8]

Even if there are measurement issues, they are not expected to be important enough to explain the AI productivity paradox.[9] However, they may affect the precise shape of the J-curve (Figure 3.2). At times of intangible capital accumulation, due to mismeasurement, we may believe that productivity is lower than it actually is. But the arrival of the productivity boom phase with the maturity of such capital investments will eventually be captured in productivity statistics.

Figure 3.2 The productivity J-curve



Source: Brynjolfsson *et al.* (2021).

The COVID-19 pandemic shock has accelerated the accumulation of intangible capital within the economy.[10] The emergence of remote working has revealed novel, efficient ways of producing output, even when inputs are restricted. For instance, restrictions on business travel have led firms and university researchers to develop new communication and collaboration models in order to keep output production as high as possible. That effectively can lead to a significant increase in total factor productivity growth in the short term, at least in those sectors where remote working is feasible (see GII 2022 Special theme by de Vries and Wunsch-Vincent and GII 2022 Tracker). However, the biggest impact of the pandemic is expected to be felt in the longer term. Social-distancing restrictions created a new reality where investment in digital technologies, as well as digital literacy, became a necessity. Work and production had to be rapidly reorganized through the digital channel. This fundamental shift has had two effects. First, it has allowed for the accumulation of intangible capital, so important for arriving at the productivity boom phase of the J-curve. Second, it has helped firms and workers understand where the benefits and costs of digital technologies can be found. As we progress along the learning curve for these technologies, it becomes ever more likely that the COVID-19 shock will leave a permanent footprint in the organization of economic relationships and productivity.[11]

Policy recommendations

Looking ahead, it is not good enough to simply explain the AI productivity paradox and then assume a passive role while waiting for the productivity boom phase to eventually arrive. Instead, we need to prioritize specific policies that maximize knowledge spillovers without hurting innovators' incentives, as well as adopting new frameworks more suited to measuring the contribution made by AI to productivity.

Knowledge spillovers have traditionally been a central objective of government policy interventions. Under a strong intellectual property regime that keeps the value of innovation high, policies whose objective is the better and wider diffusion of AI technologies can be beneficial in building the intangible capital needed for the productivity boom phase. Papers by Becker and by Bloom and colleagues illustrate how research and development (R&D) tax credits on AI investments can be a policy that works well in this respect.[12] In fact, many countries already provide additional fiscal incentives for R&D, such as by allowing an additional deduction to be set against tax liabilities. However, measures differ across countries in terms of generosity. Bloom and colleagues estimate that a 10 percent fall in the tax on R&D will result in at least a 10 percent increase in R&D in the long term. Hence, AI tax credits can lead to the better diffusion of new technologies and could promote the accumulation of intangible capital such that critical mass is reached and a productivity boom brought about.

In addition, policies are needed which focus on the supply of human capital, especially the supply of AI talent. One of the major obstacles to the diffusion of AI technologies is a lack of AI talent. Adjusting educational and training policies in order to facilitate a greater supply and variety of AI talent could prove very beneficial for advancing the technology frontier in industrial production.

In fact, AI talent is concentrated within a few superstar firms. A study by Jin *et al.* analyzes US online job posting data from Burning Glass Technologies for the period January 2010 to June 2020, finding that top employers were responsible for a high percentage of total demand for frontier technology skills, such as AI, machine learning, natural language processing, cloud computing and big data.[13] To be more specific, more than a quarter (26 percent) of all job vacancies in the last decade requiring AI skills were posted by the top 10 employers of people with AI skills, whereas the percentage for more traditional information technology skills was only 6.9 percent. A widespread adoption of AI that maximizes its knowledge spillovers, and thus its social benefits, would require smaller firms to be able to hire AI experts in order to make complementary investments in intangible capital and claim a fairer share of the benefits.

For there to be more AI-oriented social benefits from innovation, the market power failure of the last decade would need to be rectified. Market power partially explains why AI and intangible capital investments are concentrated in so few firms, resulting in a small proportion of firms being able to claim a majority of the benefits from AI technologies and advance their position in the market.[14] With currently few winners from AI, average productivity growth remains low, despite AI technologies being highly productive. A study by De Loecker and colleagues finds market power to have increased significantly in the last 15 years in every major economy in the world.[15] In fact, empirical trends in market power are particularly apparent for digital markets, according to another study using a similar methodology.[16] This study assigned an index of digital intensity to each sector, based on tangible and intangible ICT investment, purchases of intermediate ICT goods and services, and use of robots. It finds that the increase in markups from 2001–2003 to 2013–2014 is greater for the average firm within a digital-intensive sector than for the average firm within a pool of non-digital-intensive sectors.[17]

Addressing the market power failure in AI-related markets would require a combination of market regulation, competition policies and labor market policies.[18] Market regulation should set basic principles of operation, so that no one firm has an unfair competitive advantage allowing it to grow at the expense of its competitors, even though it may be more efficient in terms of production costs and the quality of its products and services. Competition policy should try to ensure regulatory principles are adequately enforced, by giving to antitrust authorities the ability to intervene in a timely manner and access to relevant information in order to evaluate any case of market misconduct. Labor market policies should embrace the flexibility that allows AI talent to flow across different firms, but should also ensure workers have adequate social protection.

It is therefore a combination of tax, education, labor and competition policies that could help the productivity boom (revival) phase of the J-curve to arrive faster. In concert with this, we need to find better ways of measuring productivity with respect to AI in the Digital Age.[19] Current measurements like GDP are inadequate, when they only factor in tangible goods and services offered at positive prices; in the digital economy, many of the intangible goods and services that increase consumer welfare, as well as create jobs and generate profit, are provided at no cost to consumers. Moreover, advancements in AI decision-making and prediction could generate novel opportunities for economic growth never thought possible.

Notes

1 "We'd better watch out," *New York Times*, Book Review, July 12, 1987, p. 36.

2 Gordon and Sayed, 2020; Van Ark *et al*., 2008.

3 Stiroh, 2002.

4 Jorgenson *et al*., 2008.

5 WIPO, 2019.

6 See https://image-net.org/challenges/LSVRC/.

7 Brynjolfsson *et al*., 2021.

8 Pethokoukis, 2017.

9 Ahmad *et al*., 2017.

10 Brynjolfsson and Petropoulos, 2021.

11 Marcus *et al*., 2022.

12 Becker, 2015; Bloom *et al*., 2019.

13 Jin *et al*., 2021.

14 Kaus *et al*., 2020; Altomonte *et al.*, 2021.

15 De Loecker *et al*., 2020.

16 Calligaris *et al*., 2018.

17 However, such findings should be treated with caution. First, how to measure markups is a topic of debate. For example, a study by Philippon (2019) finds no increase in markups and concentration within the EU. It only pointed to a sharp increase in concentration within the US market. At the same time, Traina (2018) criticizes the way that markups are measured in the literature. A study by Hall (2018) finds no evidence that mega-firm-intensive sectors have higher price/marginal-cost markups, but does report some evidence that markups grew in those sectors with a rising mega-firm intensity. The implications of increasing markups are also a subject of debate. One school of thought is that this trend captures the increase in market concentration; but it may instead refer to higher production efficiency – i.e., declining marginal costs, especially in technology-related or information-intensive markets, leading to increasing markups without necessarily any growth in prices.

18 Parker *et al*., 2022.

19 Brynjolfsson and Petropoulos, 2022.

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