The Past, Present and Future of European Productivity

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Abstract

European productivity has experienced a marked deceleration since the 1970s, with the productivity gap between the Euro area and the United States widening significantly since 1995, a trend further intensified by the COVID-19 pandemic. This slowdown is particularly concerning given the backdrop of rapid technological change, global warming, and population aging. This paper provides a long-run perspective on these issues, placing the current situation in the context of historical experiences faced by European countries. We first examine the factors that have influenced productivity fluctuations, with a focus on the post-World War II economic boom and subsequent periods of stagnation. We then consider the structural and conjunctural reasons behind the slowdown since 1995. Finally, looking ahead, we evaluate the potential of Artificial Intelligence and climate-related innovations to rejuvenate productivity.

1 Introduction

In 1995, one hour of work in the euro area countries generated an average of 47.1 dollars of GDP[2], closely matching the US level of labour productivity of 46.6 dollars. By 2019, the productivity gap between the two regions had widened to 18% in favor of the US, a divergence that further expanded beyond 20% in 2023. This growing disparity has sparked extensive discussion among scholars (Lopez-Garcia and Sförzi, 2021), market specialists (Strauss, 2024) and policymakers (Schnabel, 2024, Li and Noureldin, 2024). The debate occurs within a paradoxical context where, despite concerns over a general slowdown in productivity growth across developed countries since the 1970s, the emergence of new organization of work post-Covid-19, along with rapid advancements in artificial intelligence, promise significant productivity gains.

Productivity is the key driver of per capita output dynamics over the long term, significantly influencing living standards, welfare, and the ability to reduce average working hours without compromising consumption. Labour productivity, typically

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2 Numbers are given in constant dollars of 2015 with constant PPPs and are taken from the OECD National Accounts.

measured as the ratio of value added per unit of labour input (Y/H), represents the quotient of average income (Y/P) divided by working time (H/P). Since 1890 in the euro area, Y/H has increased by a factor of 18.8, Y/P by 10.1, and H/P has decreased by 1.8 (Bergeaud et al., 2016). This implies that through collective efficiency improvements in producing more qualitative goods and services, work hours have halved while aggregate production has increased tenfold. Remarkably, this progress occurred within a relatively short timeframe, primarily over three decades (1950-1980) in the euro area, where labour productivity quadrupled. During this period, living standards also rose, with consumption per capita tripling in real terms (Barro and Ursua, 2008), and Europeans enjoyed more leisure time, with an annual reduction of 400 hours per workers (Bergeaud et al., 2016)[3]. However, since the mid-1970s, productivity, and consequently GDP per capita, has steadily decelerated, averaging growth rates of 2.1% in the 1980s, 1.6% in the 1990s, 0.8% in the 2000s, and 0.7% in the 2010s. This observation has led to concerns among scholars regarding the potential for secular stagnation (Gordon, 2012, 2017)—a prolonged period of low growth hindered by significant obstacles, including the disappointing and diminishing returns of digital technologies. Given the historical link between labour productivity and living standards, this extended slowdown raises significant concerns for economic policy and societal well-being.

To understand this dynamic, this article analyses the evolution of productivity growth in the euro area by examining its long-term trends (the past), the current factors contributing to its slowdown and divergence from the US, and the impacts of recent crises such as pandemics, energy, and environmental challenges (the present). Additionally, it discusses the potential future impacts of Artificial Intelligence (AI) and climate change on productivity growth (the future). We argue that, despite Europe's clear potential due to its market size, quality universities, and leadership in deploying green innovation and regulation to tackle climate change, the issues that plagued Europe after the 1970s—namely its inadequate innovation policy—continue to hinder its ability to derive productivity gains from global technological revolutions. The recent development of AI, largely driven by US and Chinese actors, threatens to repeat this pattern, potentially relegating Europe to a second mover in this new technological revolution unless it can adapt its innovation policy.

A useful decomposition will drive our analysis. Many macroeconomic models assume the existence of an aggregate production function[4] that links output (GDP) to factor inputs (labour and capital) $Y = AF(K, L)$ where A is a factor neutral multiplier that captures the efficiency of the production defined as an increase in real GDP when input factor remains similar and is often named Total Factor Productivity or TFP. Under some regularity assumptions on the production function F, one can then

[3] The question of whether this reduction in the number of hours worked results from increased labour productivity, such as through automation, is a significant topic of discussion, explored in Autor and Salomons (2017). They observe that while technological advancements tend to reduce employment at the sectoral level, this effect is counterbalanced at the national level by a positive demand (or productivity) effect. This balance is explained by how increases in sectoral productivity led to higher incomes and consumption, which in turn, stimulate overall employment. See also Cette et al. (2023).

[4] Although this existence has been debated and is the subject of the famous controverse of the two Cambridges in the 1950s and 1960s (see Cohen and Harcourt, 2003 for a presentation of the question).

decompose labour productivity into the product of TFP and the volume of physical capital per unit of labour. With this definition, TFP measures the effect of technological progress on GDP as process efficiency improves (for example, a chemist discovers a new formula that allows to create a drug with half the quantity of solvent). But TFP will also capture changes in the composition of the labour force, the average level of human capital and the allocation of economic resource across economic agents, among other things. It thus remains essentially a residual factor, as defined by Solow (1956) and is by far the factor that explains most of the difference in GDP per capita across countries and half of the growth rate of GDP over the 20th century (Bergeaud et al., 2017). Examining long-run structural changes in growth, therefore, necessitates a study of TFP dynamics and a natural factor behind the current slowdown would be a deficiency in innovation, or more precisely, to a shortfall in innovations that have the potential to significantly enhance production efficiency.

A rich body of literature has explored why firms appear hesitant to invest in productivity-enhancing technologies, despite historically high expenditures on Research and Development (R&D), scientific publications, and patenting activities, which indicate that overall innovation did not decline. We consider the misallocation of production resources, particularly R&D resources, within the euro area as one potential explanation. This hypothesis suggests that significant growth and welfare improvements could be realized through well-crafted industrial and innovation policies that redirect resources towards firms capable of adopting and developing radical new technologies. We argue that European innovation from 1995 to 2019 faced similar challenges as it did since 1950, including fragmented domestic R&D policies and a lack of integration between university-driven scientific discoveries and the private sector. This has resulted in a technological focus on “mid-technologies" (Fuest et al., 2024) such as transport manufacturing, energy, and appliances, dominated by the same firms for the past three decades. With the advent of a new industrial revolution centred around artificial intelligence and the spillovers from green innovations, European countries have a unique opportunity to reshape their institutional landscape and benefit from important potential productivity gains.

The remainder of the article examines various questions surrounding the dynamics of productivity in the euro area. The first part considers the long-term drivers of productivity in European countries by analysing a variety of data spanning the 20th century. We begin with a simple accounting exercise to explore the role of demographic, technological, and institutional factors in explaining the dynamics of GDP and the differences between Europe and the U.S. We then discuss the factors that contributed to the exceptional period following WWII, which ended with the oil crisis in the mid-1970s, and document Europe's missed opportunities during the ICT revolution. In the second part, we discuss the underlying reasons behind the widening productivity gap between European and U.S. economies since 1995, and particularly since 2020, by decomposing the recent slowdown in European productivity. We distinguish between factors that are conjunctural and likely short-term, and more structural issues related to innovation policies. Finally, the last part discusses the possibility that European economies are facing a secular stagnation, where the current low GDP growth might become the new norm. We also consider the potential of two important factors—the rapid development of AI and the general effort toward mitigating climate change and fostering an energy transition—in boosting productivity.

2 Historical Drivers of European Productivity

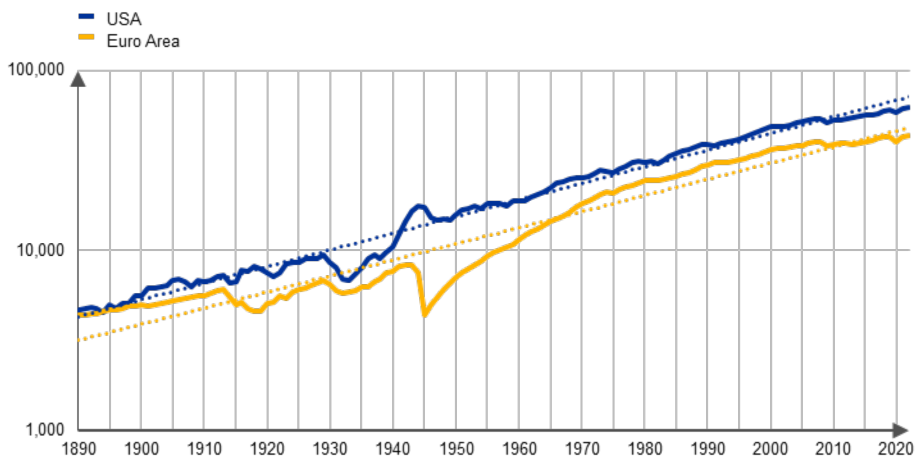
2.1 Long term growth

A well-documented fact about the US GDP per capita growth over the past 150 years is its remarkable consistency, maintaining a near constant growth rate of 2% per year. This regularity was influential in inspiring theory of growth (Jones, 2002) while at the same time, a focus on specific subperiods reveal the succession of waves of growth resulting from the diffusion of General Purpose Technologies (GPT) such as railways or electricity, which have inspired Schumpeterian growth theory (Aghion et al., 2014). Is a similar pattern observable for European countries and the euro area as a whole? Data from Maddison (2006) allows to look at this directly. Chart 1, plots the two series in constant 2015 dollars since 1890. We can clearly see that the US growth figures are indeed closely approximated by a trend line with a slope of 2.13%, with the US economy oscillating around this trend. However, this pattern does not hold as clearly for the (reconstituted) euro area, which would be represented by a trend line with a 2.06% slope, but with a lower goodness of fit. Unlike the US, the growth rate of European countries shows a distinct upward trend after World War II, which is followed and preceded by periods of more moderate growth.

Chart 1

GDP per capita in the Euro area against the US since 1890

(constant US dollars of 2015)



Sources: Long Term Productivity Project (Bergeaud et al., 2016, updated from here).
Notes: GDP per capita has been calculated yearly in national currency and then converted into constant 2015 USD using constant ppp conversion rates. The euro area has been reconstituted by backdating national accounting data with data from Germany, France, Italy, Spain, Netherlands, Belgium, Ireland, Austria, Portugal, Finland and Greece. Trend lines respectively have an R2 of 0.981 for the US and 0.960 for the euro area.

To better understand these differential dynamics and the underlying factors over such a long period, it is necessary to collect reliable data that would allow to offer an *anatomy of growth* in many countries (Madsen, 2010) and to assess the respective role of productivity, demographics, working time and accumulation of capital.

2.1.1 Growth accounting

Following the seminal work of Angus Maddison, many economic historians have provided estimations of GDP but also production factors (labour and capital) for specific European countries dating back to at least 1890 (e.g. Prados de la Escosura, 2007 for Spain, Baffigi, 2011 for Italy or Smits et al., 2000 for the Netherlands) which allows for a more meticulous analysis of the long-run development of GDP per capita and its main drivers. These datasets, harmonized by Bergeaud et al. (2016) and updated within the *LongTermProductivity* project, enable in particular a yearly estimation of TFP, measured as a Solow residual (Solow, 1956):

$$Y_{i,t} = TFP_{i,t}\, K_{i,t}^{\alpha} L_{i,t}^{1-\alpha}$$

With K the stock of physical capital, L the total number of hours worked and Y the GDP. Both Y and K are given in constant 2015 dollars and we assume a constant elasticity α across time and country. This is of course a very strong assumption, but it allows to only focus on the relative developments of K, L and Y to explain changes in TFP. This formulation is also useful to analyse the main drivers of GDP, indeed (dropping subscripts):

$$Y = P \times TFP \times \left(\frac{K}{L}\right)^{\alpha} \times \frac{N}{P} \times H \qquad (1)$$

Where H is the average working time per workers, N the total number of workers in headcount, P is population. This decomposition can be interpreted as a breakdown between a purely demographic factor (P), an efficiency factor (labour productivity equal to $TFP \times \left(\frac{K}{L}\right)^{\alpha}$, ie the product of TFP and capital deepening), a factor influenced by both age structure and labour market institutions (equal to $\frac{N}{P} \times H$, the product of average working time and employment rate). Log differentiating equation (1) allows to look directly as the different contribution of each factor in explaining the average change in GDP. The results are presented in Chart 2a for the whole 1890-2022 period and in Table 1 for chosen subperiods. In the euro area, labour productivity grew on average by 2.2% per year and the contribution of population (0.5%) is equal to the negative contribution of the reduction in working time (-0.5%) while employment rate has no trend (but this is heterogeneous across European countries). Among these 2.2%, 0.7% comes from the capital deepening, i.e., the fact that the stock of capital grew faster than labour, and 1.5% comes from an improvement in production efficiency (or TFP). In the US, the main difference comes from the population and labour input. First population increased much faster than in Europe, in particular due to immigration waves and higher fertility rates than Europe. Second, the ratio of employment over population increased by 0.2% per year and average working time per workers declined less than in Europe. On the contrary, labour productivity has the same average growth rate in both regions, although the dynamics is very different across subperiods as we analyse below.

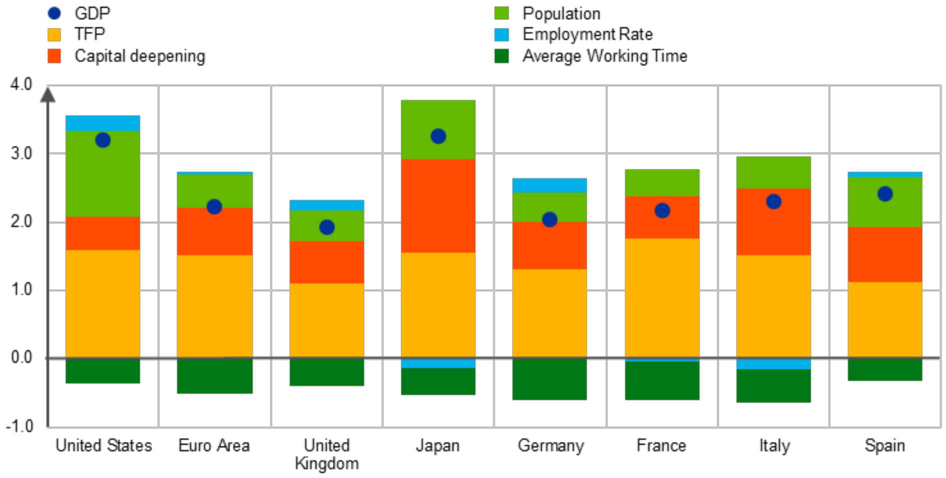
It is therefore apparent that aside from population factors, the average contributions of each element to GDP growth are notably similar across regions. However, a distinct exception is observed in the euro area's labour input utilization, which has a lesser impact on GDP growth compared to the US. This discrepancy is evidenced by a more significant negative contribution from working time reductions and a subdued positive impact from employment rates. To fully capture the variances between the two regions, Chart 2b delineates the relative differences in each factor between the euro area and the US, where, barring minor covariance terms, the aggregate of each component should align with the relative difference in GDP per capita. These illustrations clearly highlight TFP as the principal driver behind the long-term dynamics of GDP per capita. Moreover, it is evident that both labour-to-population ratios and average working hours were historically higher in the euro area compared to the US until the 1980s, after which they began to decrease relatively, contributing to the widening GDP gap between the two regions. These disparities reflect the European inclination towards allocating a substantial portion of productivity gains to reducing working hours, achieved through both diminished hours per worker and lower retirement ages. The literature offers various explanations for this choice, ranging from higher taxation and stricter labour regulations (e.g., Prescott, 2004) to cultural preferences for leisure in Europe (Blanchard, 2002). Nevertheless, post-2010, the employment-to-population ratios in Europe converged with those in the US, leaving working time as the sole differentiator[5].

[5] The aggregate dynamics shown in Chart 2b for the euro area hides important disparities across European nations. Charts A1 in the Appendix replicate this chart for Germany, France, Italy, Spain, and the Netherlands, highlighting these differences.

Chart 2
Growth accounting

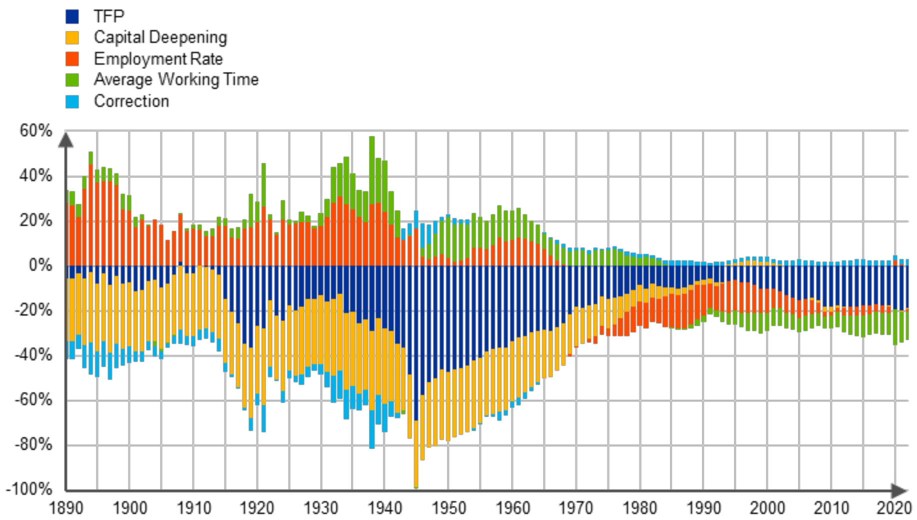
a) Decomposition of GDP growth rate. Average 1890-2022

(in %)



b) Decomposition of the relative gap between the euro area and the US's GDP per capita

(in %)



Sources: Long Term Productivity Project (Bergeaud et al., 2016, updated from here).
Notes: Chart 2a decomposes the growth rate of GDP into 5 factors following equation (1). Yearly growth rate averaged over the period 1890-2022. Chart 2b shows the relative gap between the euro area (reconstituted, see Chart 1) and the US's GDP per capita decomposed into 4 factors. The sum of bars for a given year is equal to the relative gap in GDP per capita. A negative bar means that the US has a large factor than the euro area.

Table 1
Growth rate of GDP and subcomponent by subperiods in the USA and euro area

Average growth rate per subperiods

(in %, yearly average)

USA	1890-1913	1913-1950	1950-1975	1975-1995	1995-2005	2005-2022	Total
GDP	3.6	3.2	3.5	3.0	3.1	1.6	3.2
TFP	1.0	2.5	1.7	1.0	1.7	0.6	1.6
Capital deepening	0.5	0.5	0.6	0.2	0.5	0.4	0.5
Population	1.8	1.2	1.4	1.0	1.0	0.7	1.3
Employment rate	0.4	0.0	0.1	0.7	0.2	-0.1	0.2
Hours worked per worker	-0.1	-1.0	-0.3	0.1	-0.3	0.0	-0.4
Euro area	**1890-1913**	**1913-1950**	**1950-1975**	**1975-1995**	**1995-2005**	**2005-2022**	**Total**
GDP	2.1	0.8	4.9	2.3	1.9	1.0	2.2
TFP	1.2	0.9	3.5	1.5	0.8	0.4	1.5
Capital deepening	0.5	0.3	1.5	0.9	0.4	0.3	0.7
Population	0.8	0.4	0.7	0.3	0.3	0.3	0.5
Employment rate	-0.1	-0.2	-0.2	0.2	0.7	0.4	0.0
Hours worked per worker	-0.2	-0.6	-0.7	-0.6	-0.3	-0.3	-0.5

Sources: Long Term Productivity Project (Bergeaud et al., 2016, updated from here).
Notes: Yearly growth rates in % averaged over chosen subperiods.

2.1.2 Productivity waves and industrial revolutions

In addition to being the main component behind the long-run dynamics of GDP per capita, TFP is also an important driver of the differences between the euro area and the US.

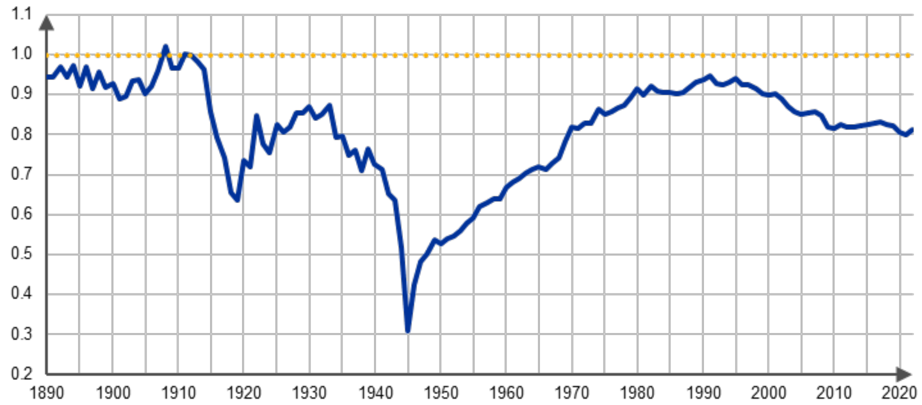
The evolution of TFP is presented in Chart A2 in the Appendix for a recomposed euro area since 1890 and its breakdown by country in terms of levels. These graphs reveal distinct economic regimes. From 1890 to WWI, Europe experienced a growth rate of TFP of approximately 1% per year and was at a level similar to that of the US, which already defined the technological frontier along with the UK (see Bergeaud et al., 2023). This trend persisted until 1939, except during the war period and the Great Depression. Notably, during the interwar years, Europe experienced a relative decline compared to the US, which underwent its first productivity wave (Gordon, 1999). The period following WWII is marked by exceptional productivity gains, averaging about 4% per year between 1950 and 1974, and a catch-up to the US level from a significantly lower starting point. After a productivity decline in 1974, the euro area reached its peak relative to the US in 1990, before experiencing a relative decline (see Chart 3a).

Chart 3

Total Factor Productivity in the Euro area against the US since 1890

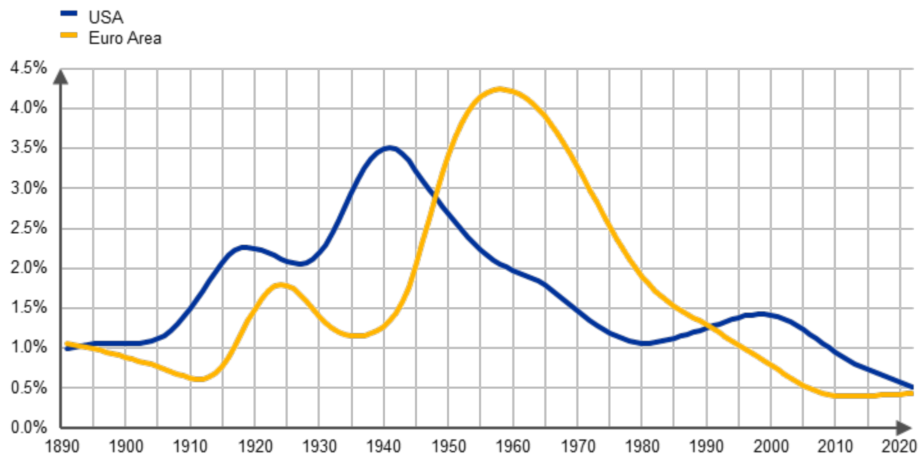
a) Ratio of TFP: Euro area against the US

(ratio)



b) Waves of TFP

(%)



Sources: Long Term Productivity Project (Bergeaud et al., 2016, updated from here).
Notes: Chart 3a reports the ratio of the Euro area over the US TFP. Chart 3b reports the filtered growth rate of TFP in both regions. This growth trend has been obtained through an HP filter with a coefficient of 1000.

To better understand the long-term shifts in growth trends, Chart 3b illustrates the filtered growth rates of the euro area and the US since the late 19th century. This representation highlights the productivity waves that drive long-term growth, reflecting various industrial revolutions (Ferguson and Wascher, 2004). Notably, the "*big wave of productivity*" (Gordon, 1999) is evident in the US from the 1930s to the 1950s, marking the diffusion of key innovations from the second industrial revolution. This period marked a transition to mass production, propelled by innovations in assembly line methods and the creation of novel manufacturing techniques (Landes, 2003). The technological breakthroughs initiated in the US post-1870s likely had a profound impact on enhancing productivity and transforming the economic landscape. While the First Industrial Revolution unfolded in Great Britain, the sequel unfolded in the United States, spurred in part by the more effective utilization of natural resources, including the employment of machinery for resource extraction. This period saw significant advancements, including widespread electrification, which notably reduced the costs of lighting and heating (Nordhaus, 1996), the introduction of electric motors offering decentralized and safer power sources, enhancements in combustion engines speeding up transportation, and breakthroughs in petrochemistry leading to significant pharmaceutical developments. The spread of these technologies was further enabled by the accessibility of affordable and efficient energy sources, particularly oil, whose consumption per capita rose from approximately 4.7 barrels annually per inhabitant in 1920 to 15.7 in 1950 (Shurr et al., 1960). These advancements not only propelled industrial and economic expansion but also revolutionized organizational and managerial practices, financial markets (Ferguson and Wascher, 2004), transportation, and prompted a shift from agricultural to service-oriented sectors, elevating levels of human capital crucial for transitioning from stagnation to growth (Galor, 2005; Squicciarini and Voigtländer, 2015) and the adoption of technologies.

In Europe, a comparable wave of productivity can be seen but did not start before the end of WW2. Indeed, a very large part of TFP gains has been made between 1950 and 1974 a period where Europe was clearly lagging behind the US and benefited from a powerful catching-up effect. This led most European countries to approach the TFP level of the US by the mid-1970s and some even briefly overtook the US (Italy, Netherlands, see Charts A2). The mechanism behind this exceptional growth, discussed more comprehensively in Section 2.2, bears similarity to the experience of the US two decades earlier. Additionally, the adoption of institutions that foster risk-taking and investment in R&D played a significant role.

Chart 3b also reveals a less pronounced wave in the US during the 1990s, corresponding with the third industrial revolution and the rise of Information and Communication Technologies (ICT). This period, extending from 1990 to the mid-2000s, saw a notable increase in productivity that has been directly linked to the integration and widespread adoption of computers and the internet in business processes and consumer behavior. The automation of manual tasks, enhanced data processing capabilities, and improved communication networks significantly contributed to efficiency gains across various sectors (Jorgenson, 2001; Fernald, 2015). However, despite the profound societal and production transformations brought about by these technologies, their impact on productivity has been considered underwhelming, especially when compared to the big wave of the second industrial revolution. In Europe, the effect was even more muted, with TFP showing no significant wave of increase, a phenomenon extensively analysed in the literature pointing towards European firms' lower investment in ICT (see van Ark et al., 2008 and Section 2.3).

2.2 What made this possible?

Current discussions predominantly focus on the recent slowdown in GDP and productivity growth. However, a broader historical perspective reveals that the 20th century was a period of exceptional growth, during which European countries increased their output per capita tenfold while simultaneously halving the average working time. Prior to addressing the long-term feasibility of such dynamics, one question is what made this exceptional number possible, especially during the 3 decades 1950-1980, which followed a period particularly damaging for continental European productivities imputable to the Great Depression and WW2. In 1950, Europe had retrieved its GDP per capita and TFP levels of 1938 but massive war destruction (estimated at 1.5% of total capital stock of the region every year from 1939 to 1945, see Bergeaud et al., 2016) necessitated extensive reconstruction across Europe and substantial investments were needed to rebuild infrastructure, industries, and cities. This reconstruction effort, fuelled by domestic and international resources (notably the Marshall Plan), provided a significant stimulus to economic activity. The rebuilding process not only replaced lost capital but often did so with more modern facilities and equipment, thereby enhancing productivity (Eichengreen, 1993).

2.2.1 Successful policies

The reasons behind the long-lasting effect of this post WW2 rebound can be explained by a confluence of factors that boil down to two categories: new institutions and adoption and diffusion of existing technologies, in particular in the manufacturing sector (Van Ark et al, 2008).

Regarding institutions, European countries followed the overarching strategy of keeping wage demands reasonable to allow for the reinvestment of profits and favour investment (Eichengreen, 2007). This led to an increase in the stock of capital that was faster than that of labour which boosted labour productivity and per capita income. In terms of product markets, the establishment of institutions such as the European Coal and Steel Community (ECSC) and the European Economic Community (EEC) facilitated economic integration, reducing barriers to trade, and increasing economic interdependence among European nations. Finally, most European countries relied on their relatively educated population and the higher education institutions inherited from the 19th century to train engineers and scientists forming the "*upper-tail knowledge*" necessary to facilitate the adoption of technologies, but at the same time, also had room for improvement given that the average European only had educational attainment at 70% of the average American. Improved secondary education attainment (for example France raised minimum school leaving age to 16 in 1959) and the replacement of older less educated generations with younger more educated one would rapidly increase the average level of human capital.

Second, European countries benefitted from a catch-up dynamic essentially through the adoption of technologies that were already well diffused in the US and developed during the 1930s and accelerated during WW2. With increasing absorptive capacities resulting from higher human capital, European firms could benefit from improved process efficiencies by using more technology advanced machineries or inputs. The extent of this domination of US technologies in Europe can be observed using patent data. Bergeaud and Verluise (2024) indeed provides a new dataset that retrieve information from French, British and German patents since the 19th century, along with the name, nature, and location of the assignee. From this dataset, we can see that patents filed in France and Germany shows that US assignees represented a raising share from below 10% to 25% (see Chart 4a) in the immediate aftermath of WW2. This increase is mostly driven by some very large firms such as IBM or General Electric or Dupont de Nemours. Chart 4b reports the share of patents from the top 10 assignees from the US as a share of total patents in Germany and in France.

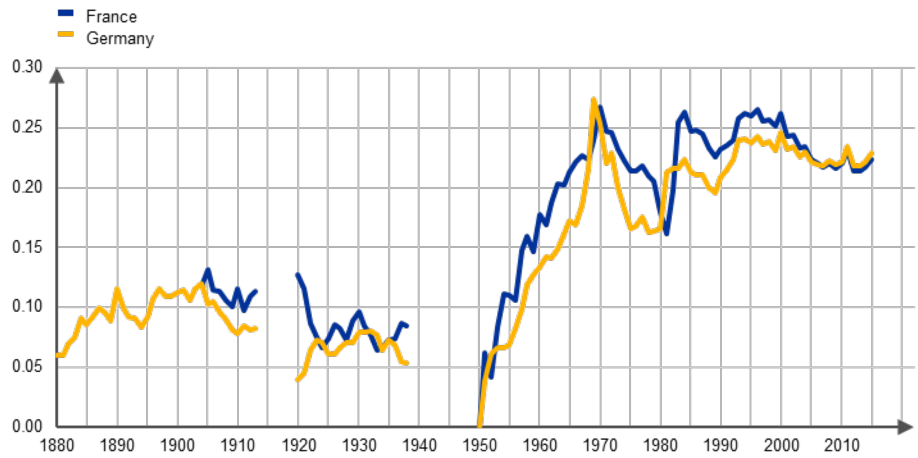
The main reason a US firm would file a patent application in a European country is because they expect to commercialize some products in the country and this increasing share of patents from superstar US firms is illustrative of the prominent role played by these actors in the European economic landscape of the 1950s. This was not without generating worry from the observed technological gaps between European firms and their US competitor in some sectors. For example, Servan-Schreiber (1967) wrote: *"The third largest industrial power in the world, after the United States and the U.S.S.R., could well be in fifteen years, not Europe but American industry in Europe."* Nevertheless, it is well documented that with international patent application and foreign direct investment in general flow ideas and knowledge (Eaton and Kortum, 1999; Aghion et al., 2023a) providing that domestic firms have the right innovation capabilities. This is what European countries industrial policy tried to achieve during the 1950s and 1960s (Owen, 2012). The approach was however different between France or the Netherlands as well as the United Kingdom who attempted to create national champions by encouraging mergers and partnerships very much supervised by the state, and Germany who relied on its pre-WW2 comparative advantage, namely in chemistry and pharmaceutical industry, a strong connexion between science and industry, namely through the Max Planck Society and the Fraunhofer Society, and by establishing competition and openness to international trade (Herrigel, 1997). These policies were to some extent successful as some European firms managed to file a large number of patents in the US by the end of the 1960s, even if this is essentially true for Germany (Bergeaud et al, 2023).

Chart 4

Patenting from US assignees in France and Germany

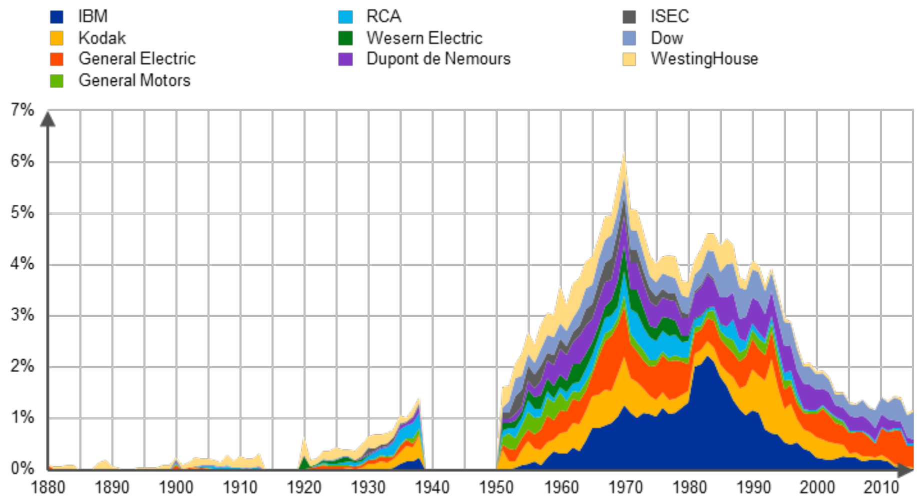
a) Share of foreign assignees in the French and German patent offices

(share)



b) Share of the top 10 foreign assignees in the French and German patent offices

(%)



Sources: PatentCity (Bergeaud and Verluise, 2024).
Notes: Chart 4a reports the share of patents with at least one assignee located in the US in the French and the German patent offices based on the publication year. Chart 4b reports the share of patents filed in the French and German patent offices over total patents where the assignee is one of the 10 US firms with the highest number of patents in these patent offices and is based in the US. Post 1978 includes patents from the European Patent Offices (EPO) when the designated state is either France or Germany. ISEC stands for International Standard Electric Corporation and RCA for Radio Corporation of America.

2.2.2 But not enough to maintain long-run growth

The rapid catch-up of most European countries halted in 1975 regarding GDP per capita and about 10 years later regarding TFP. But more importantly, the development of innovative capabilities and the adoption of more adequate economic institutions did not allow European countries to generate growth led by the development of frontier technologies, in particular in ICT, and most European countries slowed down with respect to the US from the mid-1980.

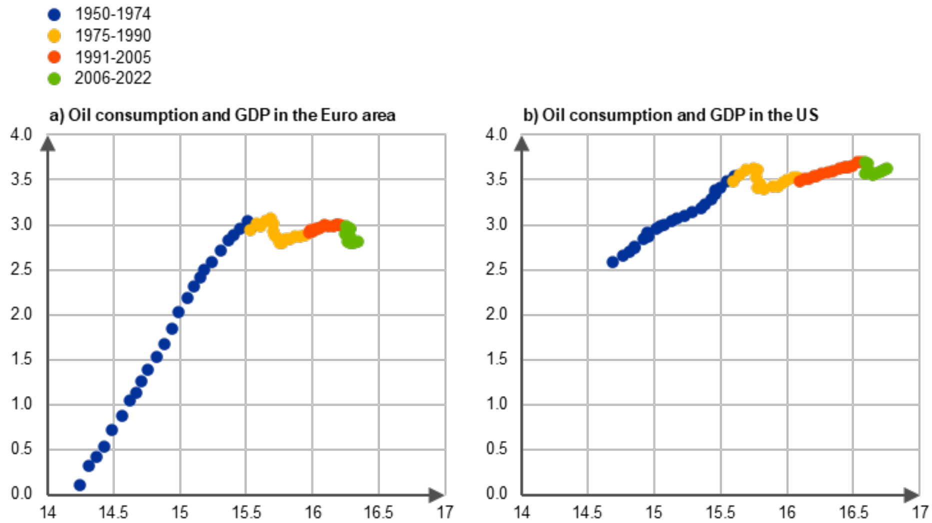
To explain this second phase of slowing TFP gains, two observations can be made. First, although some European champions managed to compete with their US counterparts as measured by the number of patents filed in the USPTO, aggregate R&D effort was much lower than what the US did in terms of R&D which reach 3% of GDP by 1960, essentially driven by federal expenditures, namely the department of defence and the NASA (Dyèvre, 2024) in the context of the Cold War and the race against USSR. As explained by Owen (2012), the American dominance in the computer and electronic industries can be traced back to the substantial demand created by military and space programs in the early post-war era and this created important spillovers to the private sectors (Kantor and Whalley, 2023; Gross and Sampat, 2023). The size of the US market was also larger than in Europe which provided American manufacturers with benefits not accessible to European companies. Finally, financial institutions and competition policy ensured that in parallel to the extreme domination of IBM, smaller companies could emerge and develop specialized minicomputers and processors including Helwett-Packard or Intel (Bresnahan and Malerba, 1997). By contrast European firms failed to favour the entry of new players and relied on partnership between states to push large projects which were negatively impacted by the strong competition of US firms (and later Japanese firms) and relied on the ability of governments to better identify the direction of technology than entrepreneurs. This first observation explains why generally Europe did not in fact turned its economy and institutions into a framework that would allow them to generate growth from frontier technologies, and in particular in ICT, the main driver of TFP growth after the 1980s.

A second observation concerns the important yet often overlooked role of oil as a cost-effective and efficient resource in the manufacturing industry. After WW2, oil became prominent in Europe and emerged as the favoured energy source across industrial manufacturing, transportation and electricity generation due to its superior energy density, versatility, price stability and ease of transport and use. This was made possible thanks to significant technological advancements in oil exploration, drilling and offshoring, which facilitated access to reserves that were previously considered unreachable. Furthermore, the strategic control exerted by Western powers and a coalition of major oil companies over the principal oil-producing regions ensured price stability. This consortium wielded significant influence over the Middle Eastern oil producers, securing a steady and affordable oil supply to meet the burgeoning industrial demands of the West (Smil, 2010; Yergin, 2011). As a result, the correlation between GDP and oil consumption is particularly strong during the period 1950-1974 in most countries, as reported in Chart 5. Jorgenson (1984) notes that the utilization of fluid energy types, like petroleum and natural gas, has enabled significant changes in production processes and geographical distribution within sectors like industry, agriculture, and transportation which has contributed to the expansion of national output and productivity. After this period, oil and GDP started to decouple brutally in Europe (see Chart 5a) following the first oil crisis and the correlation was never positive again as oil consumption per capita started to decrease in line with the shrinking share of the manufacturing sector, the implementation of policies aiming at improving energy efficiency of the production and transportation and to the diversification of energy sources to gas, nuclear and later renewable energies. These correlations are of course not proof of a causal relationship between oil consumption and growth even though a statistical analysis of the coevolution of oil price and GDP in the US suggests that some recessions are associated with major oil price increases (Hamilton, 1983; Barsky and Kilian, 2002). In addition, the high dependency of western economies to oil and the fear that supply may be disrupted was a subject of concern in Europe and in the US regarding the sustainability of GDP and productivity trends during the 1970s (IEA, 1982). The post 1973 era, and in particular the aftermath of the second oil shock of 1979 dramatically increased the relative cost of energy to other inputs such as labour (Schur, 1982) which slowed down the growth rate of capital deepening and therefore of labour productivity (see Table 1), particularly in Europe, whose domestic production was more limited than that of the US. In addition, this could negatively impact TFP through two mechanisms: firstly, by reallocating production from high-energy-intensive sectors, which are potentially more productive, to less energy-intensive sectors; secondly, by decelerating the development of labour-intensive, productivity-enhancing, and energy-intensive technologies as innovation resources are partially redirected towards the exploration of energy-saving technologies and alternative energy sources[6], including a resurgence in coal use (see Figure A3b in Appendix).

Chart 5

Oil consumption and GDP in the euro area and in the US

(log of oil consumption in y-axis and log of GDP in x-axis)



Sources: Bergeaud and Lepetit (2020).
Notes: Oil consumption is measured in quad Btu and is taken in log (y-axis). GDP is taken in log and measured in US dollars of 2015. Chart 5a considers the Euro area as the aggregate of 7 countries: Germany, France, Italy, Spain, Netherlands, Portugal and Finland, Chart 5b considers the US.

2.3 The missed ICT revolution

The divergence in TFP between Europe and the US started during the 1990s as productivity growth continues to slow down in most European countries while the US

6 Figure A3a in the Appendix reports federal expenditures from the department of energy which experienced a clear increase during the 1970s.

experienced a productivity revival. Given the extensive literature in the US linking this increasing TFP to the ICT revolution, the absence of a similar wave in Europe would suggest that the adoption and diffusion of these technologies was insufficient.

To test our hypothesis, we employ sectoral data from EU-KLEMS (Bontadini et al., 2023), which compiles sector-level input and output information. This dataset enables the estimation of labour productivity and capital stock across various countries, including specific assessments of the physical capital stock in many assets such as ICT. As an initial simple exercise, we consider data from eight Eurozone countries and for the United States, spanning from 1995 to 2019. We categorize the 32 sectors into two groups based on their ICT intensity in 1995, determined by whether their capital stock in IT, software, and communication equipment as a share of their total capital stock exceeded the median proportion.

We then aggregate the yearly level of labour productivity for each group, separately for the US and for the euro area, constructed by aggregating the eight countries. Results are presented in Chart 6 and show that the ICT intensive sector in the US experienced a much higher increase in labour productivity than in Europe, whereas the difference between the two regions are more modest in other sectors. To explore these findings further, we then exploit the panel dimension of the data and estimate the following model:

$$\log\left(lp_{i,c,t}\right) = \alpha_{i,c} + \gamma X_{i,c,t-1} + \phi_{c,t} + \psi_{i,t} + \varepsilon_{i,c,t} \qquad (2)$$

Where i denotes one of the 32 industries, c one of the 21 countries for which we have enough data and t indices the year from 1995 to 2019. The dependent variable, lp, is the level of value added in volume divided by total working time, taken in log and the main regressor X is the ratio of IT capital over total capital stock in volume[7]. $\alpha_{i,c}$, $\phi_{c,t}$ and $\psi_{i,t}$ are fixed effects. The coefficient of interest is γ which captures the effect of an increase in the share of IT capital on labour productivity. Results are presented in Table 2. We start by excluding $\phi_{c,t}$ and $\psi_{i,t}$ and simply use a year fixed effect (column 1), we then add $\phi_{c,t}$ (column 2) and finally estimate the fully saturated model with $\psi_{i,t}$ (column 3). These three models are estimated using the OLS and standard errors are clustered by sector. The marginal effect of X is always positive and significant, suggesting that increasing IT intensity is followed by a sizable change in labour productivity. However, despite the large set of fixed effects which neutralize any omitted factor that would be country or sector specific, and even if we use a lagged regressor, these models may suffer from endogeneity given the many potential unobserved factors that could impact both labour productivity development and IT intensity. We consider an instrumental variable (IV) approach where the endogenous variable X will be instrumented by Z an estimate of the declining price of IT technologies from improvements made in the US. Formally, Z is the product of three terms. First a time specific factor Z_t that is equal to the production price of the computer production sector in the US, divided by the price of

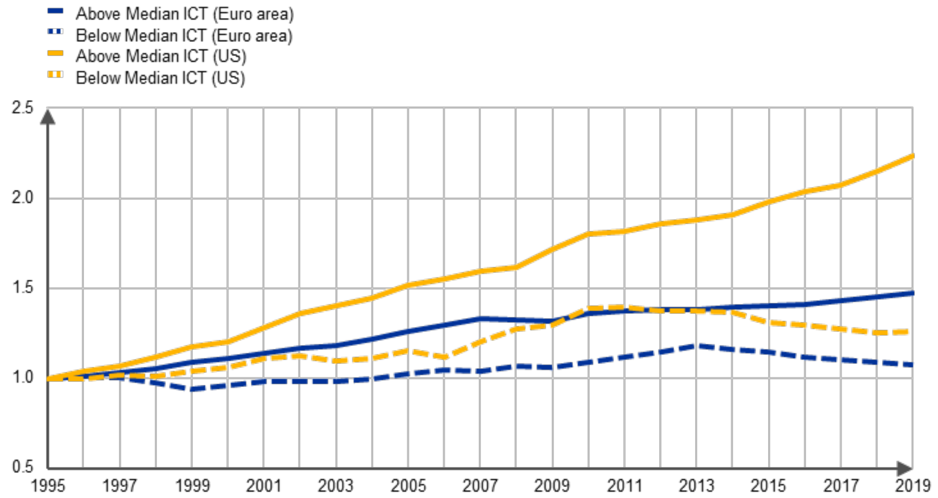
7 We restrict to IT because of better data coverage and exclude communication equipment and hardware but results are qualitatively similar with these two additional components.

value added. Second a sector specific factor Z_i that is equal to the sector specific intensity in ICT in the US in 1995, as measured previously. Third a country specific factor Z_c which is equal to the share of patents filed at the European Patent Office (EPO) before 1995, that cite a US patent in technology H (a broad technological class that includes most innovation in the field of electronics). Our instrument Z can therefore be seen as being equal to the relative price of IT production in the US weighted by a measure of the exposure of the sector to IT and of the country to the US technologies. Results are presented in column 4 of Table 2. The magnitude of the coefficient suggests that increasing IT intensity by 0.01 corresponds to a 6% increase in labour productivity compared to the sector and country average.

Chart 6

ICT and growth

(labour productivity (index, 1995 = 100)



Sources: Author calculations based on EU-KLEMS.
Notes: Labour productivity is measured for above median ICT sectors and below median ICT sectors, respectively in the US and in the euro area, which is approximated by aggregating over 8 countries: Germany, France, Italy, Spain, Netherlands, Portugal, Belgium and Austria. ICT sectors are defined based on the capital in volume in IT, Software and Computer equipment divided by total capital in volume. Aggregate labour productivity is obtained by taking the weighted average across sectors, using nominal value-added weights.

These findings indicate a causal relationship between IT investment and labour productivity improvements, revealing that Euro area countries were less efficient than the US in both adopting IT technologies massively and in leveraging them to achieve labour productivity gains. This discrepancy partially explains the observed productivity differences between the two regions since 1995. Gordon and Sayed (2020) corroborate this finding, estimating that variances in ICT investment could account for approximately 20% of the productivity growth rate gap between the US and Europe during the period 1995-2005. Similarly, Cette et al. (2022) report analogous outcomes utilizing a macroeconomic growth accounting approach, along with new data on investments in hardware, software, and robots. They find that while European firms indeed invested in these technologies, the impact on productivity was more subdued compared to that in the US over the period 1995-2019. Schivardi & Schmitz (2020) explore this issue in the context of Southern European countries, linking it to managerial efficiency (see also Bloom et al., 2012). They highlight how IT has augmented the significance of management practices and that, particularly in Southern Europe, management tends to be relatively inefficient (Bloom and Van

Reenen, 2007). Additional factors commonly cited for Europe's slow uptake of IT and ICT include the quality of digital infrastructure, such as broadband internet, particularly during the late 1990s and early 2000s (OECD, 2019), and the relatively high proportion of small firms in Europe compared to the US (Schnabel, 2024), which limits the scalability benefits of IT.

Table 2
The effect of IT intensity on labour productivity

Regression results

Dependent variable: log of labour productivity	(1) OLS	(2) OLS	(3) OLS	(4) IV
IT capital stock over total capital stock	2.774	1.690	1.658	6.608
	(0.959)	(0.777)	(0.549)	(3.136)
Observations	12,948	12,948	12,948	12,380
Fixed effects				
Sector - country	Yes	Yes	Yes	Yes
Year	Yes	No	No	No
Sector-year	No	Yes	Yes	Yes
Country-year	No	No	Yes	Yes

Sources: EU-KLEMS. 32 industries, 21 countries.
Notes: Regression results are based on estimating equation (2) using OLS for columns 1 to 3 and IV estimation for column 4. Observations consist of annual country-sector pairs from 1995 to 2019. Column 1 includes only sector-country fixed effects, column 2 adds sector-year fixed effects and columns 3 adds country-year fixed effects. Column 4 uses an instrument described in Section 2.3 and otherwise replicates the model of column 3. The associated Kleibergen-Paap F statistic is 25.6. Standard errors are clustered by sector.

The comparison of recent growth dynamics in European countries with those before 1974 underscores both current and future productivity challenges. A pivotal phase, often traced back to the mid-2000s, marks the conclusion of the ICT productivity wave and the onset of a declining productivity trend in the US and several European countries (Fernald, 2015; Bergeaud et al., 2016). This period was characterized by subdued productivity growth, subsequently leading to stagnant GDP per capita growth. The limited dynamism in TFP starkly contrasts with the widespread perception of innovation, reviving debates around the secular stagnation hypothesis (Gordon, 2012)—a prolonged phase of low growth hampered by significant challenges, including the diminishing returns on digital technologies. In subsequent sections, we will explore the contemporaneous period and examine potential explanations for the post-pandemic slowdown, before discussing the future of productivity and the secular stagnation hypothesis in particular.

3 Current productivity development in the euro area

This section examines productivity dynamics since 1995, a period marked by the widening gap between the US and the euro area, as outlined in the preceding chapter. Chart 7a shows the two dynamics using quarterly data in constant US dollars. Initially, in 1995, labour productivity levels were nearly identical in both regions, evolving to a point where, by 2005, the euro area's productivity stood at

85% of the US level. Paradoxically, the Great Financial Crisis saw an increase in US labour productivity, a mechanical effect attributed to firms disproportionately laying off low-skilled workers. This led to a quick shift in relative productivity to 80%, a disparity that was maintained up to the onset of the Covid-19 pandemic, after which the productivity trends continued to diverge further. While this divergence is exacerbated by the dramatic productivity performance of the US, a particularly concerning observation is the negative trend in labour productivity in the Euro area since the pandemic, which, when compared to the pre-pandemic trend, shows a 2.9% decrease in the level of output per hour worked in Q4 2023 (see Chart 7b).

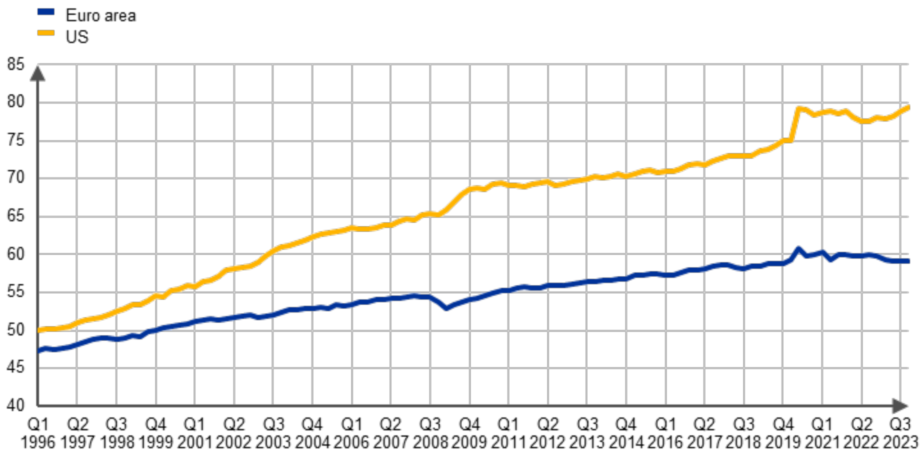
We first discuss potential explanations for the slowdown and consider the role of the pandemics and energy crisis in explaining the recent dynamics. We then discuss more structural factors explaining why productivity in the Euro area may be sluggish for a prolonged period without a change in innovation and industrial policies.

Chart 7

Labour Productivity in euro area

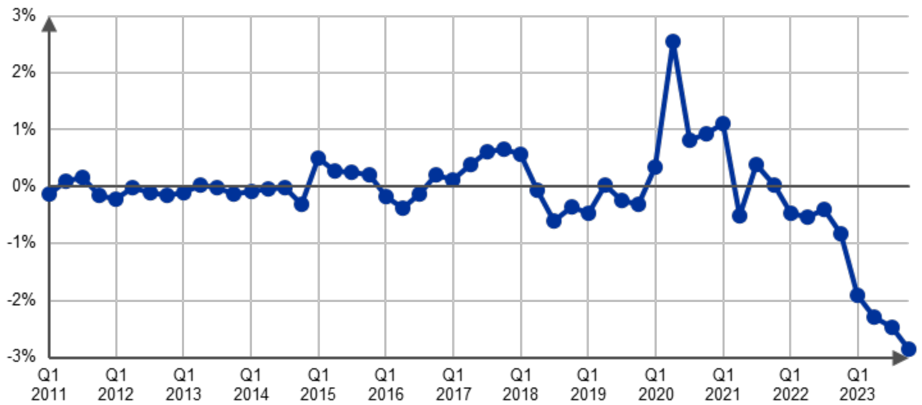
a) Labour productivity in constant dollars

(dollars of 2015 per hour)



b) Deviation of labour productivity from pre-pandemic trend in the Euro area

(%)



Sources: Bureau of Economic Analysis and Eurostat Quarterly National Accounts.
Notes: Chart 7a reports the quarterly value of GDP divided by total hours worked in the economy converted in constant US dollars of 2015 per hours. Chart 7b reports the difference between the logarithm of labour productivity in the euro area with its pre-pandemic trend, calculated between 2011q1 and 2019q4.

3.1 Anatomy of the recent slowdown

3.1.1 Sectoral decomposition

The relative decline in labour productivity in the euro area can be decomposed into the contribution of 11 different sectors and each individual country. As a first exercise, we report in Table 3 the difference between the level of sectoral value added per hours worked in the last data point we can observe (fourth quarter of 2023)[8] compared to the sectoral pre-pandemic trend. Figures A4 in the Appendix report the corresponding time series. There are notable differences across sectors: "utilities and energy" was hit particularly strongly, but represents a small share of the total economy, it is followed by construction and manufacturing and retail.

Table 3
Labour productivity in the euro area by sector

Regression results

ISIC 4 sector	Relative decline in 2023Q4 relative to pre-pandemic trend	Pre-pandemic trend (average growth rate per quarter)	Share of sector in total value added 2010-2019
Agriculture (A)	-5.3%	0.8%	1.7%
Arts, entertainment and recreation (R-U)	-0.2%	0.0%	3.5%
Construction (F)	-13.0%	-0.2%	5.0%
Finance & Insurance (K)	+2.9%	0.4%	5.1%
Information & Communication (J)	-2.4%	0.9%	4.6%
Manufacturing (C)	-4.6%	0.7%	16.8%
Professional services (M-N)	+1.0%	-0.3%	11.2%
Public administration (O-Q)	+0.1%	0.1%	19%
Real Estate Activities (L)	-2.4%	-0.1%	11.3%
Retail (G-I)	-3.6%	0.4%	18.8%
Utilities, Mining and Energy (B and E)	-24.8%	0.5%	3.2%

Sources: Eurostat Quarterly National Accounts
Notes: Pre-pandemic trend is calculated by fitting a linear trend on the logarithm of labour productivity between 2010q4 and 2019q4 using the OLS. Public Administration corresponds to sector "Public administration, defence, education, human health and social work activities" (ISIC 4 O to Q). "Arts, entertainment and recreation" corresponds to sector "Arts, entertainment and recreation; other service activities; activities of household and extra-territorial organizations and bodies" (ISIC 4 R to U). "Professional services" to "Professional, scientific and technical activities; administrative and support service activities" (ISIC 4 M and N). "Retail" corresponds to "Wholesale and retail trade, transport, accommodation and food service activities" (ISIC 4 G to I).

On the other hand, certain sectors, notably finance and services, have exhibited productivity levels surpassing their pre-pandemic trends. Another useful decomposition of aggregate labour productivity involves distinguishing between an average effect and a reallocation effect (also known as a shift-share decomposition). The former quantifies changes in the unweighted average level of labour productivity, while the latter assesses the potential gains from the reallocation of market shares: if more productive sectors expand more rapidly than less productive

8 The official publication of quarterly data for 2023q4 was early April 2024. It is important to note that at the time of the study, the numbers were still flagged as "provisional".

ones, the overall impact on productivity is positive, even if average productivity remains static. Historically, since 1995, the contribution from the reallocation component across these 11 sectors has been considerably lower than that from within-sector effects. Nevertheless, considering the severity of the 2020 shock, there might have been significant reallocation across sectors. This hypothesis can be formally evaluated using the Olley and Pakes decomposition, as detailed in Melitz and Polanec (2015).[9]

$$y_t = \sum_{i=1}^{N} y_{i,t} s_{i,t} = \bar{y_t} + Cov(y_{i,t}, s_{i,t}) \quad (3)$$

Were $y_{i,t}$ is the logarithm of the labour productivity of country i in quarter t and $s_{i,t}$ is the market share measures in terms of value added[10]. We calculate these quantities for the euro area and analyse their growth rates, comparing their levels with the trend from 2010 to 2019. The results, presented in Figure A5 in the Appendix, indicate a positive contribution from the relocation component and a negative contribution from the average change in labour productivity. Notably, the relocation shock intensified during the pandemic as more productive sectors, particularly finance and ICT, expanded relative to others that stagnated. This observation aligns with findings reported in the United States (Barrero et al., 2021a). However, this trend did not reverse post-2021; the reallocation component continued to exceed its pre-pandemic trend, while average sectoral productivity declined.

3.1.2 By country

Not all euro area countries followed a negative productivity trend and an exploration country by country shows that France stands out as being particularly negatively impacted by the pandemics as shown in Chart 8. In this graph, we can see that the level of labour productivity in France is still 8% below its pre-pandemic trend and about 4% below its 2019 level. Among the other large countries, Germany, Italy and Spain are between 1 and 2% below their pre-pandemic trend while Netherlands is 0.5% above. The impressive decline of France’s productivity compared to other countries has been partly linked to labour market programmes aiming at reducing unemployment through subsidized contracts and structural reforms that increased the participation rate of less productive workers (about 3% according to Devulder et al., 2024).

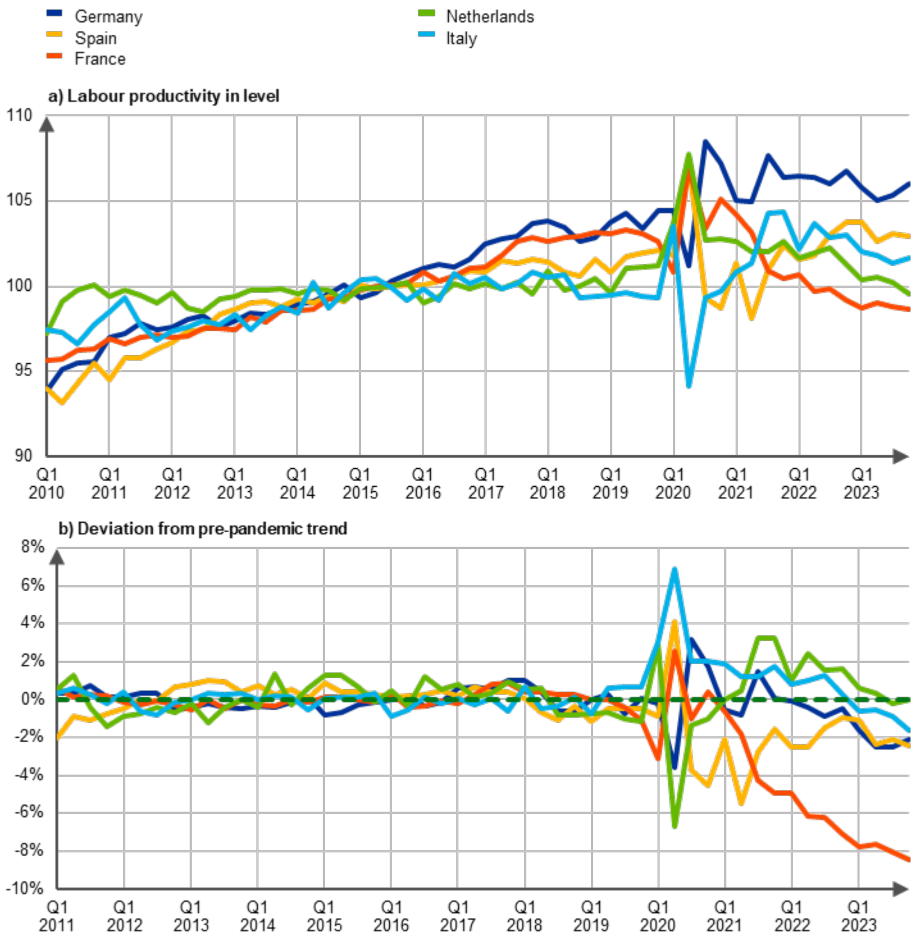
9 The use of aggregate data does not allow to compute a dynamics Olley and Pakes decomposition as in Melitz and Polanec (2015) without information on entry and exist which are therefore integrated in both the covariance and average terms.

10 Using alternative weights: hours or nominal value added does not change the result.

Chart 8

Labour Productivity in 5 euro area countries

(index 2015=100) / (%)



Sources: Eurostat Quarterly National Accounts
Notes: Chart 8a reports the quarterly value of GDP divided by total hours worked in the economy standardized by its value in 2015. Chart 8b does the same as Chart 7b but for the 5 largest euro area countries separately.

Beyond the specific case of France, a decline of labour productivity means that total labour supply increased faster than output. This can be a consequence of a decline in unemployment, such as the one observed in the euro area since the mid-2010s if the average productivity of unemployed workers is lower than the average productivity of active workers. This is however a temporary negative impact as these workers will gain in efficiency as they gain more experience and training.

3.1.3 Short-term explanations

A recent article by Lesterquy et al. (2024) investigates productivity loss within the French manufacturing sector by surveying managers from a representative sample of 2,000 firms. The manufacturing sector, constituting approximately 17% of the total economy's value added, is not only more productive than the service sector but also offers higher wages. It is intricately linked to international trade and heavily dependent on natural resources. The primary causes of productivity loss in 2023, as identified in the study, relate to negative shocks following the lockdown—specifically, disruptions in Global Value Chains (GVC). Additionally, the report highlights the impact of rising energy prices. These factors similarly affect production; both compel workers and managers to expend more time and resources to identify new suppliers and adapt their processes to higher input prices. However, high adjustment costs often preclude effective adaptation to such fluctuations. In extreme cases, the escalating energy costs, coupled with a shortage of inputs and prevailing uncertainty, can lead to temporary plant shutdowns, severely hampering production.

These negative impacts on production would only affect aggregate labour productivity if the reaction of working time to these shocks was less pronounced than that of value added. To directly assess this, we utilize quarterly data from the Eurostat short-term indicators on production and employment for the manufacturing sectors. Although these indicators are less precise than national accounts data, they enable near real-time measurement of production and labour developments in narrowly defined sectors. We measure exposure to international trade by calculating the share of imports of intermediate inputs and capital goods sourced from the BRIICS countries (Brazil, Russia, India, Indonesia, China, and South Africa) relative to the total imports of these goods by firms in a given sector and country, based on 2019 data. We then estimate the following model:

$$\log\left(PROD_{i,c,t}\right) = \alpha_{i,c} + \gamma X_{i,c} \times T_t + \phi_{c,t} + \psi_{i,t} + \varepsilon_{i,c,t} \quad (4)$$

Where $PROD_{i,c,t}$ measures production of sector i in country c during quarter t, $X_{i,c}$ is the share of import from BRIICS defined in 2019 for a given pair of sector and country and T_t is a dummy variable equal to 1 after 2020q1. γ therefore measures the marginal impact of *X* on the dynamics of production after the pandemics. The inclusion of sector-time and country-time fixed effects implies that γ will compare different countries within the same sector over time, controlling for both global sectoral trends and country-specific economic conditions. There are 18 countries and 27 manufacturing sectors and we exclude the year 2020 from the estimation. Results are presented in Table 3. Column 1 directly estimates equation (4), column 2 replaces the measure of production by a measure of total working time and column 3 by a measure of employment (headcount). Results are presented in Table 4: Column 1 directly estimates equation (4), Column 2 substitutes production measures with total working time, and Column 3 uses employment headcount. The consistently negative and significant coefficient indicates that connections to large exporting countries outside Europe before the pandemic are associated with greater reductions in activity post-2020. The coefficients suggest that a 1 percentage point increase in imports share decreases production by approximately 1.4%, hours worked by 1%, and employment by 0.8%. This impact is more pronounced on production, consequently affecting labour productivity.[11] Notably, the effect is stronger on the intensive margin of labour, consistent with adjustments in average

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[11] Lalinsky et al. (2024) analyse the impact of COVID-19 on productivity and highlight the doubly negative effect of GVC disruptions. These disruptions not only disorganize production but also disproportionately impact larger firms engaged in international trade, which are typically more productive.

working time discussed in the following section. Columns 4 to 6 do the same but only consider exposure to Russian exports, the qualitatively similar results suggest that long disruption of value chains have a negative impact on productivity but also that the measured effect could be driven by energy products. Chart A6 in the Appendix shows that indeed, sectors that are above the median in terms of their typical consumption of energy products have experienced a decline of their production while other sectors did not.

Table 4
Exposition to international trade, production, and labour input

Regression results

	(1) Production	(2) Hours Worked	(3) Employment	(4) Production	(5) Hours Worked	(6) Employment
γ	-1.406	-0.968	-0.817	-1.129	-0.804	-0.731
	(0.499)	(0.446)	(0.313)	(0.508)	(0.490)	(0.306)
Number of observations	36,749	34,579	35,588	36,749	34,579	35,588
Adjusted R2	0.816	0.790	0.771	0.816	0.790	0.771

Sources: Eurostat short-term indicator in the manufacturing sector and OECD STAN Bilateral Trade Database by Industry and End-use category database.
Notes: OLS estimation of equation (4) for different dependent variable: production, hours worked and employment. The coefficient γ measures the marginal effect of a one unit change in the share of import from BRIICS countries (Brazil, Russia, India, Indonesia, China and South-Africa) in 2019 in columns 1, 2 and 3 and only from Russia in columns 4, 5 and 6 after 2020 compared to before 2020. The unit of observation is a pair of sector-country and is measures at a quarterly frequency. There are 18 countries and 27 manufacturing subsectors. Each column includes a set of country-sector, country-year and sector-year fixed effects. Standard errors are clustered at the sector level.

Why would employment react less than output to negative shocks? Labour markets in the euro area have demonstrated an impressive resilience after the pandemics and the following crisis. Unemployment continued to decline and reached a historically low point in many countries while at the same time the number of vacancies continued to increase leading to an unprecedented market tightness. This sustained tightness has prompted firms to engage in labour hoarding, retaining employees to avoid the high costs and risks associated with cyclically adjusting their workforces—costs that are exacerbated by stringent European labour regulations compared to those in the US and by the historically high hiring difficulties reported by firms (Bergeaud et al, 2022a). Firms are therefore more reluctant to let go their workers, in particular the most skilled workers. A new indicator calculated by Eurostat (Gayer et al., 2024) shows that in Germany and France, 15% of firms are hoarding labour, 5 percentage point higher than before the pandemics.

These channels are likely to impact productivity only in the short to medium term. As energy prices decrease and firms identify new suppliers to restore their value chains, production is expected to increase faster than employment, leading to a rise in labour productivity. However, other factors may exert more permanent effects.

3.1.4 Structural factors on the labour input

The study conducted by Lesterquy et al. (2024) also highlights several structural factors contributing to the decline in productivity in France (and likely to be relevant for the euro area as a whole), including difficulties in hiring and retaining skilled workers, absenteeism, and a general lack of workforce engagement. The issue of skill mismatch was recognized before the pandemic and is commonly underlined as an important factor behind the low investment in ICT by European firms (OECD, 2019). According to Eurostat, in 2022 over 60% of European companies attempting to hire ICT specialists reported significant challenges in filling these positions, either due to a scarcity of applications or because the offered salaries did not meet applicants' expectations. This situation reflects a mismatch between the supply and demand of specific skills, exacerbated during periods of rapid technological advancement. Despite improvements in educational levels and increased worker training, the swift pace of technological change diminishes demand for certain skills, compelling workers to accept less productive roles that are resistant to automation or to engage in the gig economy (Goldin et al., 2024).

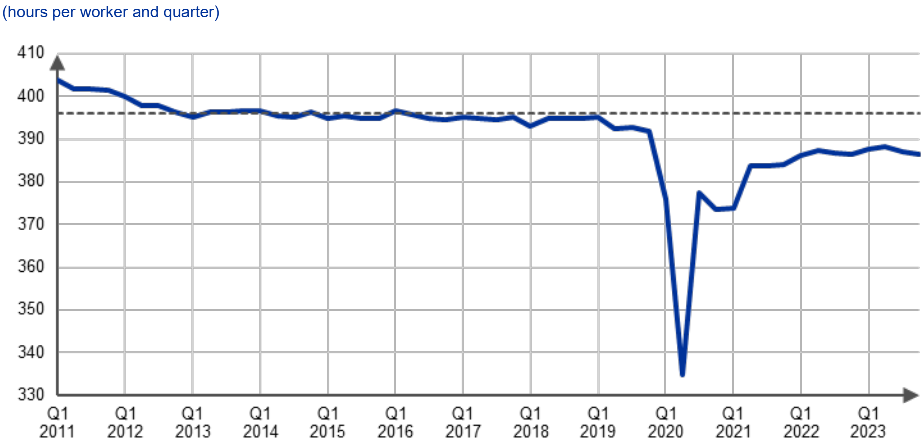
The second issue of diminished workforce engagement is more challenging to test quantitatively. Arce et al. (2023) document a reduction in average working hours per worker, as evident in Chart 9. This trend is compounded by increased sick leave, which remains above pre-pandemic levels in many countries, and a shift towards part-time employment, both of which contribute to reduced actual working hours.[12] However, it is unclear whether these changes result from a shift in worker preferences during the pandemic, as suggested by the rise in resignations since 2021,[13] and are part of long-term trends where average hours worked have been declining in Europe since the 1990s (in contrast to the US), or directly result from the ongoing crisis. This could include COVID-19 waves or firms adjusting labour inputs in response to economic uncertainty. Although Arce et al. (2023) challenge the hypothesis of changed worker preferences by pointing out that a significant proportion of workers would prefer more working hours, it is also possible that the observed workplace fissurization—characterized by decreased promotion prospects and increased workplace loneliness as noted by LeMoigne (2020)—and declining job satisfaction are exacerbated by global shocks like COVID-19 and associated lockdowns.

[12] These sick leaves, as well as number of days off, should in theory be included in measured working time but are not always straightforward to quantity. Similarly, if workers decide to use as many days off as they can (for example by using compensatory time off or banked hours) this may lead to an overestimation of working time by national statistics and ultimately to an underestimate labour productivity.

[13] For example, in France, the number of resignations is historically high with almost 500,000 resignations of workers with permanent contracts in 2023 according to the ministry of labour (DARES).

Chart 9

Average working time in the euro area



Sources: OECD Quarterly National Accounts
Notes: Average hours per worker and year is calculated over all employees. The horizontal line represents the average value between 2011q1 and 2019q4.

The disappointing effect of teleworking?

The onset of the pandemic and the ensuing shift toward remote work have spurred discussions on potential economic gains from new work arrangements, as noted by Barrero et al. (2023) and Criscuolo et al. (2023). Several mechanisms suggest that teleworking could enhance productivity: 1) extended work hours due to reduced commuting time (Barrero et al., 2020), 2) decreased real estate costs per worker (Bergeaud and Ray, 2020), 3) upgrades in IT and communication equipment alongside modernized management practices, 4) a shift of labour and capital towards larger, more productive firms that implement teleworking (Barrero et al., 2021a; Bergeaud et al., 2023), and 5) increased individual efficiency from home-based work (Bloom et al., 2015). Despite these factors, teleworking has not significantly boosted labour productivity in Eurozone countries enough to offset the negative impacts arising from other factors.

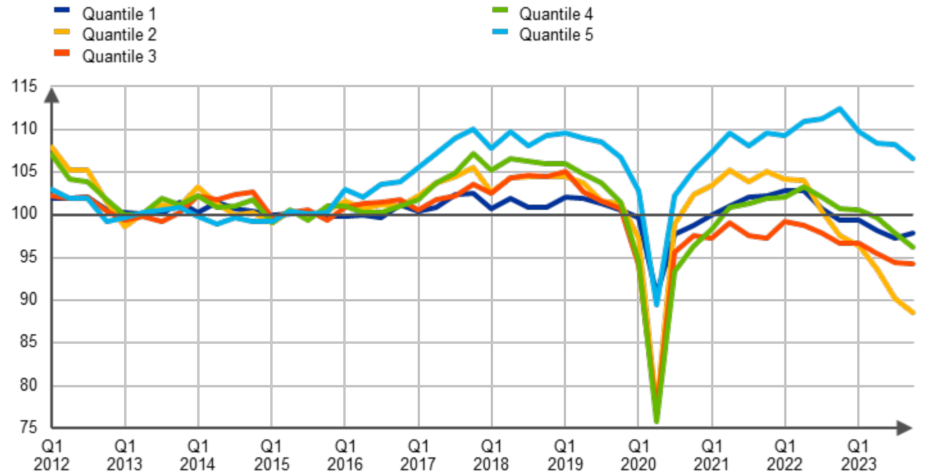
The impact of the first point about longer work hours due to reduced commuting times is ambiguous. Commuting time in Europe averages about 50 minutes, similar to the US's 54 minutes, but is typically shorter in large cities where teleworkable occupations are concentrated. Nevertheless, it is unclear if the time saved from commuting in Europe will necessarily be used to extend work hours as has been observed in the US. The second point highlights potential cost savings from reduced real estate expenses, as real estate costs are significant and rising for firms, especially in large cities (Bergeaud and Ray, 2020). Bergeaud et al. (2023) found that in 2019, firms in France that adopted teleworking used on average 3 square meters less per employee, equating to about 1500 euros saved per employee annually in cities like Paris. However, these cost savings may have been mitigated by the ongoing housing and energy crises. The third point has not materialized as expected, as the proportion of investments in ICT equipment to total gross fixed capital formation in Europe did not increase significantly after 2020. The fourth point involves the reallocation of labour and capital towards more productive teleworking firms. Barrero et al. (2021b) report that a notable share of workers would consider changing employers if not permitted to telework, which could exacerbate hiring challenges for non-teleworking firms and diminish their market share. To illustrate this reallocation effect, we use the 'teleworkability' index developed by Dingel and Neiman (2020) for the US and adapte it to the Euro area. We then use the monthly production index in the manufacturing sector and split the sectors into 5 groups of equal size based onthe extent of teleworkability, which is itself based on the workforce composition. Chart 10 illustrates that sectors in the top 20% for teleworkability were more resilient during the 2020 recession and exhibited greater dynamism post-2021, even though this trend was already present before the pandemic. It is important to note that the Dingel and Neiman (2020) index measures the potential for teleworking, which may differ from the actual intensity of teleworking, hence a reallocation toward these sectors could exacerbate this positive impact.

Lastly, regarding the fifth point on individual productivity, improvements may not have been as substantial as anticipated due to suboptimal management practices. While workers report increased focus when working from home (Criscuolo et al., 2023), they also express concerns over the frequency and length of online meetings and a lack of interaction (Barrero et al., 2024), which may hinder idea generation and contribute to workplace loneliness.

Chart 10

Production and teleworking

(index (2015 = 100))



Sources: Eurostat short-term indicator.
Notes: Each of the 157 manufacturing sectors for which we can measure production in the short term indicators is assigned an index of teleworkiability based on Dingel and Neiman (2020) and a crosswalk between European NACE sector codes and the ISCO classification. We then construct 5 groups of equal size based on this value and calculate the average (unweighted) index of production which is equal to 100 in 2015. We then report this average production every month from 2012q1 to 2023q4.

Perhaps more importantly, teleworking is not as widespread in Europe as it is in the US or the UK, with the actual number of days worked from home being lower than what employees desire (Aksoy et al., 2022). Should employers and employees reach a new equilibrium that embraces more frequent work from home, along with adaptations in management practices, materials, and office spaces, it could activate these productivity channels in the future, potentially leading to significant gains.

Zombification due to Covid support policies?

Another potential explanation for the weak productivity performance in the euro area could be the misallocation of production factors resulting from the survival of low-productivity firms, supported by policies during the pandemic and eased financial constraints. In theory, economic downturns cause less productive firms to exit the market first. This "cleansing mechanism" reallocates resources to more productive firms or new entrants, enhancing aggregate productivity through creative destruction. However, the primary goal of pandemic support measures was to reduce failures when a significant portion of the economy was forced to halt to mitigate virus transmission. These supports were only gradually phased out due to ongoing crises, resulting in bankruptcies in the market sector remaining below the pre-pandemic trend until the end of 2022 in the euro area, and only rising above trend thereafter. If public policies during the pandemic negatively impacted the entry of young, potentially innovative firms, this would exacerbate two decades of slowing business dynamism (Bundesbank, 2024).

In a preliminary exploration of this question, Lalinsky et al. (2024) analyse granular data across countries and sectors and demonstrate that the distribution of wage subsidies, loan guarantees, and tax moratoria in 2020 did not disproportionately benefit firms with low productivity prior to the pandemic, aligning with findings by Guerrini et al. (2024) in France and Bloom et al. (2022) in the UK. However, their research also indicates that higher-productivity firms exited support schemes earlier, suggesting that by 2021, support was increasingly allocated to less productive firms. Despite this shift, the rate of new firm entries remained consistent with pre-pandemic trends in the euro area and the decline in productivity does not seem to be driven by a negative reallocation effect. The dynamics of the number of bankruptcies, increasing above their trend from the end of 2022 suggests that in any case, the economy is correcting for this artificially low number of exits as support gradually expire and the long-lasting effect of such dynamics is likely to be low, although the progressive availability of firm level data will bring more direct insights.

Many of these underlying reasons behind the fact that the euro area is diverging below its pre-pandemic trends suggest that this divergence may be resorbed in the near future. This analysis is supported by recent predictions by the IMF within their Spring 2024 World Economic Outlook, which forecasts a return to 1.5% yearly growth in GDP for the euro area by 2025. As supply chain disruptions abate and energy prices stabilize, alongside diminishing effects from pandemic-related supports and decreased unemployment rates, productivity is likely to catch-up with its trend.

3.2 Lack of innovation

The preceding section discussed the impact of the post-2020 pandemic crisis on productivity in the euro area. Given the ongoing transitional period, diagnosing the precise impact remains complex without waiting for more disaggregated data to be available. However, the growing divergence from the US suggests that the current slowdown may be an extension of negative trends existing before 2020, particularly pronounced in Europe. Among the components of labour productivity, TFP is most likely driving these long-run trends and has notably slowed since the late 1970s in the euro area, with a marked decline relative to the US since the 1990s. Fernald et al. (2023) support this hypothesis with data suggesting that the observed GDP slowdown in many countries may be more attributable to enduring structural trends than to the transient effects of the recent pandemic, highlighting the need to identify structural causes.

A sluggish dynamism in TFP is indicative of an innovation deficit and insufficient investment in productivity-enhancing technologies. However, this view is challenged by the fact that R&D expenditures have not declined and reach around 2.3% of GDP in the euro area, and the number of researchers continues to rise steadily (Bloom et al., 2020). Additionally, as China increasingly contributes to the production of ideas—a resource considered "*infinitely usable*" and which can flow across borders (Jones, 2023a)—one would expect a boost in worldwide productivity growth. This apparent paradox could be explained by a declining productivity of research, where (good) ideas are becoming harder and more costly to find, and the ideas that are discovered are not easily integrated into productivity-enhancing processes or products, leading to high adoption costs. Another explanation could be the inefficient allocation of R&D across firms, coupled with excessive market power that diminishes the incentive to innovate and suppresses creative destruction. While the former explanation reflects deeper structural issues that are common across countries, the latter stems from innovation and industrial policies that fail to address the nuances of ICT and digital technologies. These technologies rely on intangible assets which generate fewer knowledge spillovers and provide leading firms with competitive advantages, ultimately stifling growth (Aghion et al., 2023b; De Ridder, 2024).

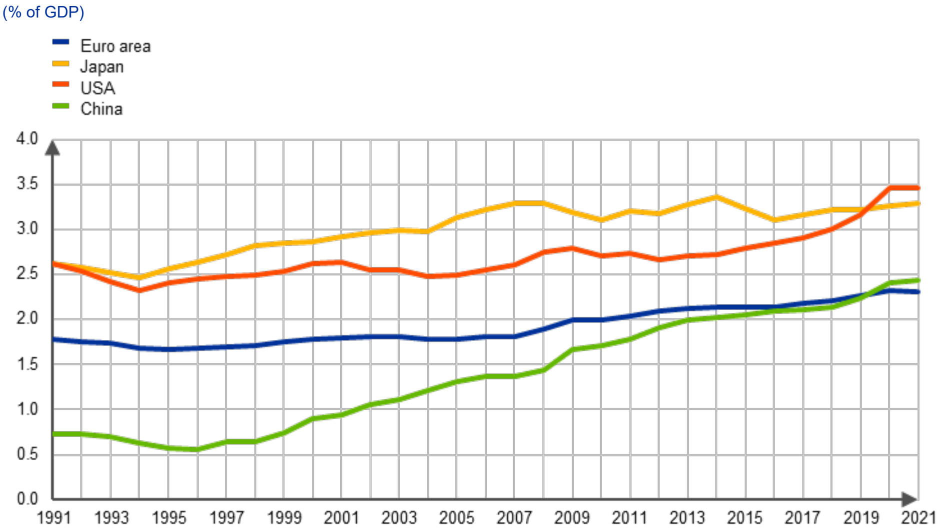
In this section, we discuss the state of innovation in Europe, in particular regarding new technologies and then discuss how innovation policy could be improved to help Europe escape its current relative decline in the innovation race.

3.2.1 Measuring innovation in Europe

In 2021, the euro area as a whole spent 2.3% of its GDP on R&D expenditures, this amounted to around 265 billion of euros spent both by the public and private sectors. Only three countries: Germany, Austria and Belgium, spend more than 3% of their GDP, a level that was set as a goal by Europe 2020 strategy objective. This share of GDP has been trending upward since 1991 when it was equal to 1.8% of GDP but is still below the level of the US or Japan and has been caught up by China in 2019 (see Chart 11).

Chart 11

R&D expenditures in the Euro area, China, Japan and the US



Sources: OECD Science and Technology indicators.
Notes: R&D includes both private and public R&D expenditures.

The gap with the US is not the result of a lack of public investment in research, the euro area spent 0.8% of its GDP in public R&D in 2021, similar to the US, but to an underinvestment by firms. Using data from Eurostat, Fuest et al. (2024) shows that the main difference between the two regions is in fact concentrated in sectors that are usually referred to as "*high tech*" such as software, computers and biotechnologies, whereas European firms actually invest more in sectors that are defined as "*middle tech*" such as automobile, chemical and transportation. Indeed, in 2019, slightly more than 50% of business R&D investment by euro area countries[14] firms are allocated in the sector "Manufacture of electronic and optical products, electrical equipment, motor vehicle and other transport equipment" against around 30% in the US and only 9% and 8% were allocated to ICT and pharma against 27% and 18% in the US respectively.

Analysing patent data presents a similar picture. When considering Patent Cooperation Treaty (PCT) families[15], a measure of patent count which is more immune to home bias and are generally regarded as a reliable benchmark for comparing different countries, we find that euro area countries were responsible for 13% of the total number of applications in 2019—with Germany and France contributing over 60% of this total—compared to 18% for the US, 16% for Japan, and 20% for China. While this share has decreased since the late 1990s in favour of China, the reduction has not been dramatic (see Chart 12a). However, when restricted to high technologies (ICT, biotechnology and nanotechnology) this share is

[14] This only includes Germany, Italy, Spain, Belgium, Austria, Portugal, Finland, Ireland and Greece as other countries (especially France and Netherlands) do not report comprehensive R&D business expenditures broken down by sectors. However, these numbers are consistent with those of Fuest et al. (2024) based on reports from the largest 2500 companies in the world.

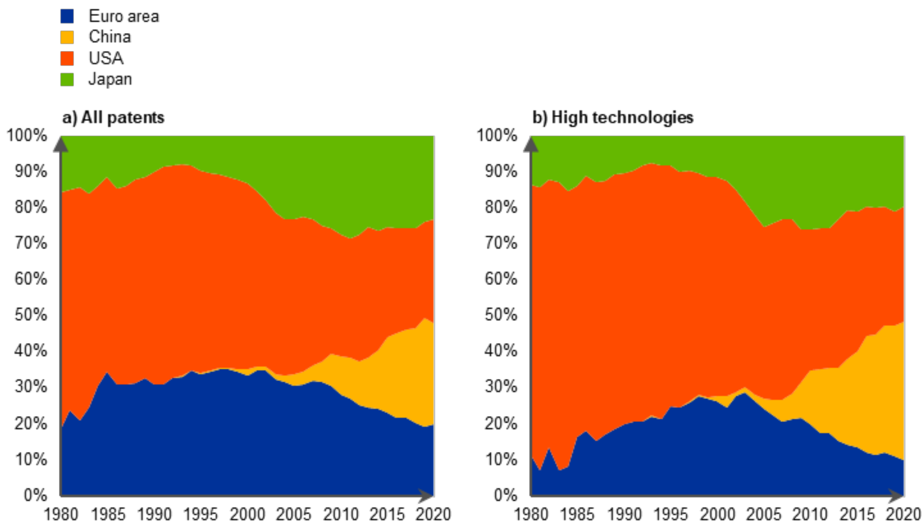
[15] A PCT application is part of an international patent system that allows inventors to seek patent protection simultaneously in multiple countries through a single application, streamlining the process and reducing costs associated with obtaining patents in different jurisdictions.

much smaller (less than 9%) and has been shrinking since the beginning of the 2000s (Chart 12b).

Chart 12

PCT family applications by region and technology

(% of total)



Sources: OECD Science and Technology indicators.
Notes: PCT family are allocated to a country based on the location of the assignee. Only patents assigned to an euro area country, Japan, the US and China are included.

Another way to document this middle tech trap in which European firms seem to be stuck can be seen in Table 5. In this table, we partition the total number of patents into 122 technologies based on the first 3 digit of the IPC technological classification. Each technology is then grouped into 8 different categories. We then count the number of PCT patent applications with assignees in the euro area, US, China, Japan or any other countries and look at which region is leading based on the greatest number of patents in 2019. We can clearly see that taken as a whole, euro area firms are filing more patents applications in categories B, D, E and F which corresponds to transport, textile, construction and mechanical engineering, whereas the US and China dominates in physics which includes most of the ICT and digital technologies.

Table 5

Leading countries by technological classes

IPC	A	B	C	D	E	F	G	H
Name	Human Necessities	Performing operation and transporting	Chemistry & Metallurgy	Textiles & Paper	Fixed Construction	Mechanical Engineering	Physics (includes most ICT)	Electricity
Euro area	2	13	2	4	4	7	0	0
US	9	8	6	1	1	2	5	0
China	2	7	1	1	0	3	6	2
Japan	1	7	8	2	1	4	2	3
Other	1	1	3	0	1	1	1	0

Sources: Google Patents Public Dataset.
Notes: This table displays the number of IPC (International Patent Classification) 3-digit subgroups where the countries listed are leading in terms of the number of PCT (Patent Cooperation Treaty) applications filed. The data is categorized by the broader one-digit IPC classes, each representing a different sector of technology. Each cell indicates the count of 3-digit IPC subgroups where the corresponding country has filed the most PCT applications relative to other countries, within the specified one-digit IPC class. Data are taken in 2019. Location of the patent is based on the location of its assignee. Patents with multiple assignees and multiple 3 digit IPC class are allocated using a fractional count.

Hence the euro area seems to have a double innovation problem: firms do not invest enough into R&D compared other countries and innovation investment and effort seem to be overly allocated to sectors outside high technology.

3.2.2 A case study of six disruptive technologies

We illustrate these issues and the particular characteristics of European innovation through six recent disruptive technologies. Utilizing the methodology developed by Bergeaud and Verluise (2023), we retrieve patents associated with specifically defined technologies by combining machine learning techniques and human validation. A significant challenge with patent classifications is their inability to precisely reflect the technology concepts commonly used by economists and policymakers. Instead, these classifications are functionally oriented, primarily serving engineers, R&D personnel, and IP specialists (Griliches, 1998). This new approach allows for a more accurate analysis of technologies and allow to look precisely at their development, we illustrate this using six examples across various economic sectors: additive manufacturing, blockchain, computer vision, genome editing, hydrogen storage, and self-driving vehicles.

We look in details at the contributions made by European countries in pushing the frontier of these technologies compared to three other regions: the US, Japan and China.[16] To measure the respective contribution of each region, we initially count the number of utility patents filed by innovators in this region. We restrict to priority applications of patent families that are filed through the PCT and count the number of patents filed at the US, Europeans, Japanese, and Chinese patent offices in each technology. For each technology, we document the proportion of patents published

16 Formally, we compare patents filed at the US Patent Office (USPTO), Japan Patent Office (JPO), Chinese Patent Office (SIPO) and in individual European countries patent offices and the European Patent Office (EPO). Because of the EPO, we cannot separate euro area countries from other European countries such as the UK, Sweden and Switzerland which account for a non-trivial share of total patents in these technologies.

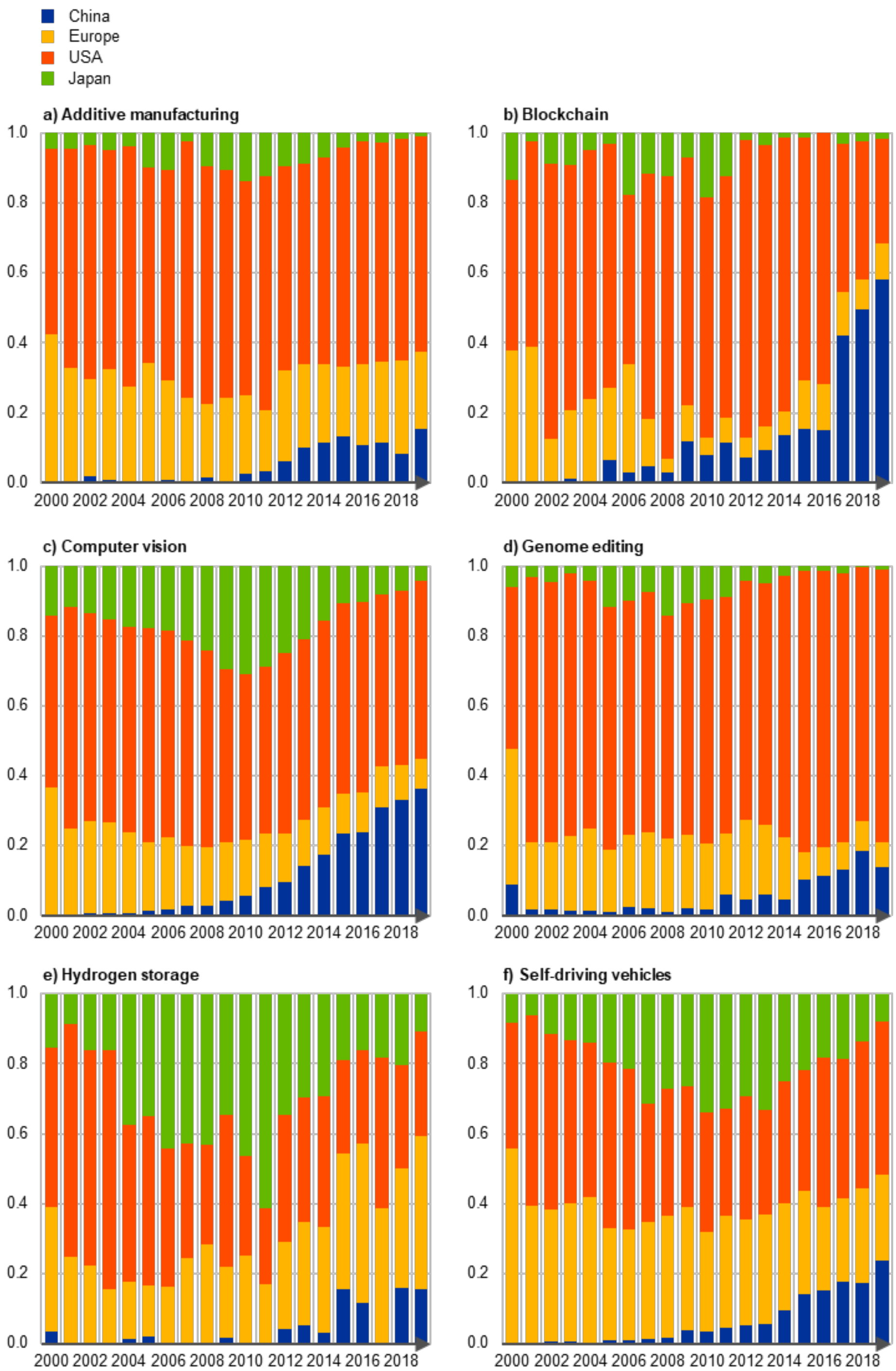
by these four offices in Figure 13 which clearly illustrates how Europe and Japan are losing shares to China. More precisely, in computer vision and blockchain, the current technological landscape is dominated by the US and China, US firms file most of the patents in genome editing and Europe and Japan continue to hold a significant number of patents in hydrogen storage and to a lesser extent in additive manufacturing and self-driving vehicles.[17] Europe does therefore continue to push the technological frontier in these technologies that are very novel and related to climate change and the future of transportation, but is no almost non-existent in the two digital technologies considered and in genome editing.

[17] The impressive Chinese performance rightfully cast doubt in the inflation of Chinese patents that have been discussed intensively in the literature (Hu and Jefferson, 2009). The restriction to PCT patent families should however mitigate this issue by selecting more valuable patents. The results are also unchanged when patent count is weighted by a measure of novelty as defined in Kelly et al. (2021).

Chart 13

Share of patents in chosen technologies

(% of total)



Sources: Bergeaud and Verluise (2023) and Google Patent Public Dataset.
Notes: Share of total patents within a PCT families in six technologies identified following the procedure of Bergeaud and Verluise (2023). European patents include patents from every European countries including the UK, Switzerland and Norway as well as the European Patent Office (EPO).

However, an interesting aspect of European countries is highlighted in Table 6, which shows the academic papers cited by patents in each of the six technologies as relevant prior art. A significant proportion of these papers (about 30% when considering the affiliation of the scientist at the time of the publication, but this share increases to 40% when we look at the affiliation history) originate from researchers based in European universities. This observation supports the notion that while Europe is still capable to generate cutting-edge research, European firms lack the capabilities to integrate these inputs into their R&D production functions and to convert them into marketable innovations. Given that these research findings are published and accessible, they are therefore utilized and developed further by firms in other countries.

Table 6

Origin of ideas of patents in disruptive technologies

	USA	Japan	China	Europe
Additive Manufacturing	51.1%	5.7%	2.7%	28%
Blockchain	53.7%	4.5%	3.9%	22.7%
Computer Vision	53.5%	5.3%	2.5%	26.5%
Genome Editing	57.3%	4.8%	1.3%	29.3%
Hydrogen Storage	34.9%	11.6%	6.3%	29.4%
Self-Driving Vehicle	49%	6.1%	1.7%	28.2%

Sources: Scopus and PatCit (Verluise and de Rassenfosse, 2020).
Notes: Share of non-patent literature citations from patents associated with each of the six technologies in rows to articles published by scientists working in institutions located in the USA, in Japan, in China or in Europe. We considered the current affiliation at the time of the article publication.

3.2.3 Misallocation of R&D

Results from previous parts show that European public support to R&D is not unsignificant and that research universities are able to produce relevant knowledge, but at the same time Europe failed to produce a technological champion in digital technology and ICT more generally. This could be indicative of a misallocation of R&D resources.

In 2023, the top 5 US firms in terms of number of PCT applications were Qualcomm, Microsoft, Apple, Google and IBM. In 2000, the top 5 US firms were: Procter and Gamble, 3M, General Electric, DuPont and Qualcomm. Doing the same exercise in Europe, the top assignees in 2023 are: Bosch, Ericsson, Philips, BASF and Bayer, while in 2000 it was Siemens, Bosch, Ericsson, Philips and BASF. There results echo those of Fuest et al. (2024) based on the EU industrial R&D investment scoreboard that report a lack of renewing of top European R&D spending firms and the strong focus on technologies the automotive industry, with leaders that have been around for decades.

Why were these large European innovators not challenged by new innovative players in the digital industry or in pharmaceutical sector as we saw in the US? As Aghion et al. (2016) demonstrated, firms typically invest in technologies where they already lead and do not deviate from this path dependency without public intervention or external shocks. In contrast to their European counterparts, U.S. firms in sectors such as transportation, appliances, mechanics, and chemistry were the main R&D investors in the 1990s and early 2000s but gradually shifted their focus towards the ICT sector. Companies like Google and Apple massively invested in hardware and software as their core activities, while others, including Starbucks and Walmart, invested heavily in digital platforms and data-backed innovations to enhance their logistics (see Aghion et al., 2023 for further discussion). This shift was supported by rapid TFP gains in the ICT and software producing sectors, amplified by the positive externalities from R&D clusters that integrated large firms, startups, universities, and capital venturers. These clusters not only promoted entrepreneurship (Delgado et al., 2010) but also enabled firms to rapidly develop innovative capabilities in emerging technologies that are typically developed in universities (Mohnen and Hoareau, 2003; Valero and Van Reenen, 2019). This dynamic environment contributed to the rapid evolution and adoption of digital technologies in the US, contrasting with the more conservative innovation approach observed in Europe.

Europe also has technological clusters, but less numerous and less intensive in R&D that what is observed in the US. For example, the most top NUTS1 region in terms of R&D over GDP in Europe is less R&D intensive that the top 6 US states in 2022. R&D expenditures are not available for smaller regional entities but using the geolocation of PCT families, one can compare European NUTS3 regions and US counties. Sorting these areas based on the number of PCT families per capita in 2022 shows that the top 25 regions include 15 that are in the US, 6 are in Germany 3 in Switzerland and 1 in the Netherlands. There are also clear differences in terms of financing of innovation that is more focused on venture capital rather than debt financing in the US compared to Europe, which tend to favour investment into digital technologies that relies a lot on intangible investment which are harder to collateralize (see Aghion et al., 2018 for a review and Garcia-Macia, 2017 for an empirical analysis).

The role of research universities is also a source of important differences between Europe and in the US. Europe also has leading research universities that produce breakthrough knowledge, as evidenced in the previous case study in Table 6. However, firms are insufficiently connected to these universities and the R&D programmes are not designed with the view of improving this connection. For example, Bergeaud et al. (2022b) shows that in France, the R&D tax credit, which does not target specific sectors and offer each firm up to a certain time a fixed tax credit based on its R&D expenditure is overly targeted to firms in the manufacture of motor vehicles and air transportation manufacturing. They compare this to a policy which subsidies applied research done in universities and found that the spillovers such policy generate in fact favoured firms in biotech, experimental development, communication equipment and manufacture of electronic component.

Finally, the role of the financial sector in shaping the allocation of R&D across firms is also crucial in explaining the differences between the US and Europe. Banking-based financial systems, like those predominant in Europe, tend to be more conservative and less inclined to invest in disruptive and high-risk innovations, particularly for young firms. This investment approach can stifle the growth of high-tech sectors and contribute to the differential allocation of R&D between the US and Europe. It also poses significant challenges regarding the development of green technologies, as discussed in Section 4.3. Fragmented capital markets in Europe further exacerbate this issue, as the lack of a unified financial market creates barriers to efficient capital allocation (ECB, 2020). Unlike the US, where integrated and highly liquid capital markets facilitate the reallocation of savings into the funding of innovative ventures, European firms often struggle to secure adequate financing for R&D activities. Moreover, the underdevelopment of the venture capital industry in Europe poses a significant barrier to innovation. Venture capital is crucial for funding startups and early-stage companies that drive technological advancements (Hall and Lerner, 2010). The future development of a more integrated capital market union and investment products that can be sold across the continent (Letta, 2024) are steps in the right direction that could improve the financing of innovative projects and the reallocation of R&D.

3.2.4 What can innovation policy do?

Universities play a crucial role in fostering innovation in the US, as evidenced by causal studies such as those by Azoulay et al. (2019a) and Hausman (2022), but generally speaking, the public funding of innovation through government agencies has been pivotal in developing radical and risky innovations. Dyèvre (2023) highlights the significant role of Advanced Research Projects Agencies (ARPA) in the innovative success of American firms and long-term TFP dynamics. Similarly, Gross and Sampat (2023) demonstrate how substantial US federal investments during WWII had a lasting impact on private innovation and the formation of local technology clusters, a mechanism also reported by Kantor and Whalley (2023) during the Cold War space race. More recently, the effectiveness of public agencies like the National Institute of Health (NIH) during the COVID-19 pandemic in quickly mobilizing resources and collaborating with startups and universities to develop a vaccine was documented by Kiszewski et al. (2021).

These instances of positive R&D spillovers from ambitious government-led projects have led many scholars, such as Bloom et al. (2019), to advocate for more “moonshots” or mission-oriented projects. These projects are supported because they drive critical technological innovations needed to address urgent global challenges like climate change or the energy transition, where market failures, such as the path dependency of dirty innovations highlighted by Aghion et al. (2016), are prominent. They also reallocate R&D resources to economic actors capable of benefiting from such programs, unlike broader R&D tax credits that discriminate based on observable firm characteristics such as size, sector, or age, regardless of their innovation potential (Aghion et al., 2024).

However, as emphasized by Fuest et al. (2024), the operations of ARPA, described by Azoulay et al. (2019b), differ from comparable European agencies like the European Innovation Council, which focuses too narrowly on technologies close to commercialization and does not favor high-risk, high-return projects.

Finally, the institutional landscape significantly influences the location choices of innovative firms, particularly in the digital industry. Unlike traditional sectors reliant on physical capital, the digital industry primarily depends on intangible assets, which are easier to relocate to more innovation-friendly environments. Demirer et al. (2024) highlight that the EU's General Data Protection Regulation (GDPR) has notably increased data storage costs in Europe, leading to a 26% reduction in data storage and a 15% decrease in data processing activities among European firms compared to their U.S. counterparts, rendering them less data-intensive. Similarly, Fuest et al. (2024) report that the relative profit margins of firms involved in high-tech sectors in Europe, compared to mid-tech firms, are much lower than in the U.S., which can be attributed to different tax systems and labour market regulations. Adjusting the institutional landscape involves balancing regulations that protect consumers and prevent market dominance—a relative success in Europe as documented by Philippon (2019)—with the need to foster the development of digital technologies that heavily rely on data and intangible assets. Europe's level of risk aversion seems significantly larger than in the US and is reflected in these institutions but also represents a significant risk of being stuck in the middle technological trap. Finding the right balance will become increasingly crucial as the development and adoption of AI technologies become central to firm growth and require dramatic societal changes.

4 Future Challenge for European's productivity

Previous sections have outlined Europe's disappointing productivity performance while acknowledging significant opportunities for improvement through targeted R&D in productivity-enhancing technologies and better designed innovation policies. This section discusses the future of productivity by first reviewing the secular stagnation hypothesis before examining two pivotal fields—Artificial Intelligence and Green Innovation—and evaluates the conditions under which they may potentially elevate Europe's economic performance as these technologies continue to advance and gain traction.

4.1 Secular stagnation

The secular stagnation hypothesis posits that the economy may endure a prolonged period of negligible or no economic growth due to persistent shortfalls in demand, alongside challenges in achieving substantive productivity improvements. Considering the long-term evolution of growth and productivity in European nations depicted in Section 2 and the recent slowdown, this hypothesis seems plausible, with the positive dynamic trajectory of productivity growth being historically restricted to a short period. The literature has identified several possible mechanisms. For example, the fact that ideas were getting harder to find (Bloom et al., 2020), or that the ICT boost may have ultimately reduced the incentive to innovate by giving some superstar firms too much market power (Aghion et al., 2023b; De Ridder, 2024). On the other hand, techno-optimists (e.g. Brynjolfson et al., 2021) argue that the pattern of productivity growth typically includes a phase of slow growth prior to a technological boom, significantly enhancing productivity, similar to the impact witnessed with electricity. This perspective suggests that the diffusion of General Purpose Technologies usually spans several decades (David, 1990) during which productivity is usually low.[18]

One argument initially put forward by Gordon (2012) is that the risk of secular stagnation reflects a supply-side problem. Gordon suggests that the most transformative innovations have already occurred, and that the technologies emerging from the third and fourth industrial revolutions do not possess the disruptive impact of earlier advancements. IT-intensive sectors, especially in the US, where these technologies were more widely adopted, experienced a productivity surplus during the 1990s. However, since 2004, despite a 1.5-fold increase in the number of patents filed with the USPTO and a 1.3-fold increase at the EPO between 2004 and 2019, there have been negligible TFP gains in the US manufacturing sector and only minimal gains in most European countries (see Chart A7 in the Appendix). This appears surprising, as manufacturing is an industry where significant productivity improvements from enhanced robots and machinery—which incorporate more efficient IT—might be anticipated. One potential explanation is that the surge in patenting activity is predominantly driven by technologies that are less conducive to productivity enhancements. For instance, Rachel (2022) proposes a model that explains the shift in R&D towards technologies oriented towards leisure. Although challenging to verify formally, this claim aligns with the evolution in the degree of novelty of technologies, as analysed by Kelly et al. (2021), who assess how the text of patents differs from those filed previously in similar technological fields.

Another potential explanation of this new “Solow Paradox” is that while technologies exist, and while their productivity potential has been proven (Gal et al, 2019), their adoption continues to be insufficient by firms and individuals due to several headwinds and inadequate institutions (Andrews et al., 2016). In particular, bad management practices, lack of ICT skills, and suboptimal job matching, alongside market access, competition, and resource reallocation policies (Andrews et al., 2018).

The lack of novel radical productivity-enhancing technologies and the slow diffusion of existing digital technologies could be seen as issues that are reversable. However, Gordon (2012) argues that the existence of several headwinds will make it unlikely: demographic: an aging population will both create an excess of savings relative to investment (Baldwin and Teulings, 2014) and depress the average worker’s productivity (Gordon, 2017), human capital: increasing further the level of education and human capital has decreasing returns and now that a large share of the working population has completed secondary education and done some college, increasing human capital is much more costly. Other headwinds include the high level of public and private debt and environmental constraints, in particular the

18 Note that these explanations for the weak dynamics of labour productivity predominantly focus on the contribution of TFP. Yet, the contribution of capital deepening since the Great Financial Crisis in Europe is also disappointing, notably as a result of weak investment following the euro area crisis. The literature has linked these performances, in particular, to financial fragmentation, policy uncertainty, and subdued demand (OECD, 2016). The massive inflow of public investments that followed pandemics since 2020 could however reverse this trend.

question of how to substitute polluting, carbon-based, source of energy and production process by clean and efficient alternatives.

In the next two sections, we examine two critical factors that could influence the secular stagnation hypothesis. Firstly, the remarkable development and rapid diffusion of AI could herald significant productivity improvements, with some proponents suggesting that AI might be the new General Purpose Technology sparking a new industrial revolution and a subsequent wave of growth. Secondly, the constraints imposed by climate change and the urgency to allocate resources towards combating global warming and reducing our environmental footprint could potentially hinder long-term growth. However, substantial investments in green innovation might lead to important spillovers, providing firms with novel ideas that could unlock new growth opportunities and overcome the difficulty to find new ideas with adequate innovation policies.

4.2 Artificial Intelligence

The recent development of various models of Generative Artificial Intelligence, capable of creating text, images, or videos from simple inputs and responding to questions with remarkable flexibility since 2022, has sparked discussions about whether we are entering a new era. In this era, the potential of computers, fueled by extensive data, could be vastly amplified. Many questions previously associated with ICT and digital technology waves have re-emerged in the debate: which types of jobs are at risk of being automated, which workers will benefit or lose out from the development of AI, what the effects on productivity will be, and what types of tasks AI can now efficiently assist and complement human work, among others. While many of these questions remain unanswered, insights from existing literature on the impact of ICT and robotics help frame the discussion by identifying relevant channels, accelerators, and obstacles. However, as with any technological wave, the initial question is whether AI will diffuse rapidly and under what conditions. We begin by exploring this question in the context of Europe and subsequently apply the recent framework proposed by Acemoglu (2024) to provide some preliminary estimates of the productivity gains potential from AI over the next decade.

4.2.1 AI innovation in Europe

Measuring AI adoption and innovation is inherently complex due to the ambiguous boundaries defining AI technology and the widespread nature of the underlying technologies. Despite these challenges, various reports highlight a significant and widening gap between the US and Europe in terms of AI investment and innovation. For instance, the 2024 AI Index report by Maslej et al. (2024) reveals that in 2023, the US had generated 61 notable machine learning models, compared to 15 in China, 8 in France, and 5 in Germany. The disparity in private investment into AI is even more pronounced, with the US investing 67 billion dollars, whereas Germany and France each invested less than 2 billion, and Europe as a whole (including the

UK) invested 11 billion. This data underscores the leading position of the US in AI development and the considerable investment gap facing Europe.

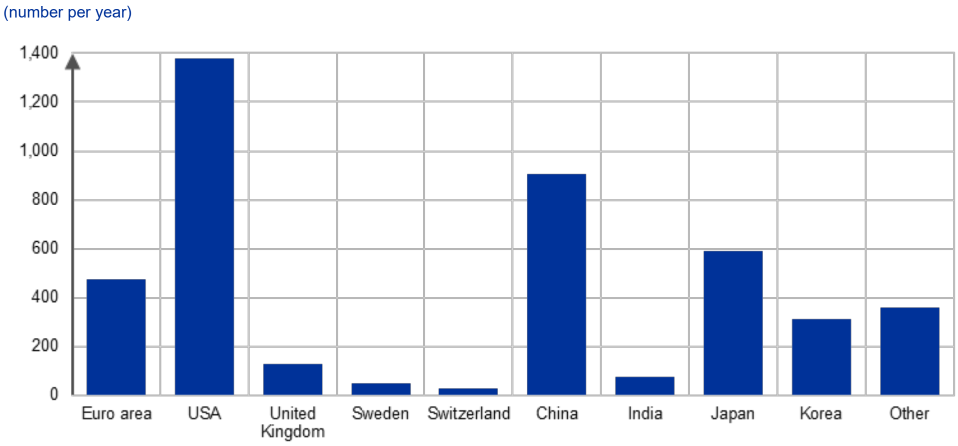
To gauge the development and level of AI innovation in Europe and compare it with other regions, examining patents appear as a natural approach. Unfortunately, directly identifying AI-related patents is challenging due to the absence of a systematic label assigned by intellectual property offices (Baruffaldi et al., 2020). To navigate this issue, we adopt a strategy that utilizes two criteria. Firstly, although AI patents are difficult to pinpoint, research papers rooted in AI are more readily identifiable. We leverage the Marx and Fuegi (2020, 2022) patent-to-paper citation database, and select papers published in journals and conference proceedings that are unequivocally within the domains of Artificial Intelligence, Machine Learning, and Computer Vision. Specifically, we include proceedings from three influential AI conferences—UAI, NeurIPS, and ICML[19]—and journals with titles incorporating terms such as “Machine Learning,” “Artificial Intelligence,” “Computational Learning,” “Data Mining,” “Neural Network,” “Deep Learning,” “Intelligent System,” “Computer Vision,” and “Natural Language Processing.” We further enrich this selection with historically significant academic papers, as determined by their citation numbers on Google Scholar, resulting in a total of 50,911 different papers cited across 19,972 patents. Secondly, we consider the presence of very specific IPC technological classes within a patent, based on a review proposed by Baruffaldi et al. (2020), as outlined in their Table 4.7.

Through this method, we identified 106,867 PCT patent families filed globally from 2002 to 2022, representing 2.68% of the total, with this share growing over time to nearly 4% by 2022. This increasing trend highlights the significant and growing impact of AI technologies in the patent landscape. Looking more in details, Chart 14 reports the average yearly number of AI patents for several regions and for individual euro area countries. The euro area as a whole filed on average 475 patents per year, around 3 times less than the US and twice less than China. Germany, France and Netherlands are the three largest contributors, but Finland and Ireland patent relatively more compared to their size.

19 Respectively the Conference on Uncertainty in Artificial Intelligence; Neural Information Processing Systems and International Conference on Machine Learning.

Chart 14

AI patents by regions



Sources: Author's calculation and Google Patent Public Data.
Notes: Average number of PCT applications filed by year between 2002 and 2022 in the field of Artificial Intelligence in selected regions. Patents have been selected based on a procedure described in Section 4.2.1.

In the field of AI and broadly in computer science, innovation often transcends commercial boundaries, making patents a less effective metric for measuring advancements. Many pivotal breakthroughs, such as attention-based transformers—which underpin ChatGPT and many other large language models—were introduced through academic papers. Google researchers, for instance, published the foundational paper on transformers and made the technology freely available, catalyzing widespread adoption and further innovation. A review of journal publications within AI highlights the significant contributions of different regions, with the US leading in citation-adjusted publications—12.5 million for the US and 7.9 million for China, compared to 7.7 million for the entire euro area (see Chart A8 in the Appendix).[20] Moreover, a distinct characteristic of the AI research landscape in the US, as noted by Maslej et al. (2024), is the larger proportion, 14%, of publications emerge from private companies compared to 9.5% in Europe and 7.4% in China, while government based institutions are more prevalent in European AI-related publications. This fact is corroborated by a manual check of the affiliations of authors of the 10 most cited AI papers of all time since 2013 which shows that private companies, in particular Microsoft and Google are overrepresented and suggests that private firms have a comparative advantage at producing fundamental knowledge that will have high impact and will diffuse more broadly (see Table A1 in the Appendix).

Similar to other digital and breakthrough technologies presented in section 3.2.2, European firms invest less in AI innovation compared to their American and Chinese counterparts but compete in producing the underlying knowledge. This disparity, as Bianchini and Ancona (2023) suggest, is not due to a lack of public effort but rather issues akin to those faced in the post-WW2 era (see section 2.2), notably a lack of coordination in industrial policies. This misalignment hinders the emergence of

20 Numbers are taken from the March 2024's version of the Country Activity Tracker of the Emerging Technology Observatory and count all academic papers published since 2013.

European tech giants capable of competing across all parts of the value chain with American superstar firms, contributing to the talent exodus to the US and the frequent acquisition of promising startups by larger foreign entities. However, the scale of investment observed in the US indicates that public spending alone cannot bridge this gap. For Europe to catch up, there needs to be an adjustment in the private financing of AI and other novel technologies. Encouraging venture capital investment and enhancing the mobility of financial capital across countries are crucial steps in building a more robust ecosystem for AI development in Europe.

Although European AI-producing firms may not be able to produce innovation at the same pace as their US-based competitors, this does not imply that other European firms are not adopting existing AI technologies. According to the 2024 AI Index Report by Maslej et al. (2024), the proportion of European firms reporting the use of AI technologies saw a significant rise in 2023, nearly matching that of North America (57% compared to 61%). This increase in adoption marks a notable shift from the patterns observed with earlier digital technologies, likely tied to the relatively low adoption costs of AI products. These products can often be seamlessly integrated into existing digital infrastructures. For instance, Microsoft's Copilot, embedded within well-established software like Excel, exemplifies how AI can be incorporated with minimal disruption, reducing the barriers typically associated with adopting new technologies. As we will see in the upcoming section, the adoption of readily available AI services can rapidly automate some tasks and enhance productivity (what Acemoglu, 2024 call *easy-to-learn tasks*). However, a more profound and structural integration of AI into production processes may require more time. Such an integration demands the development of specific skills and capabilities not just for using AI tools, but for innovating within the AI space itself. For this second wave of a deeper integration of AI within the production system, being able to develop a strong ecosystem of AI producing firm will be particularly critical.

4.2.2 Growth effect

Automation and growth

There are multiple ways in which AI can impact economic growth. Firstly, AI can boost individual workers' productivity by automating routine tasks. Similar to digital technologies, it is unlikely that AI will replace every aspect of a worker's role; instead, it will substitute specific tasks, allowing workers to reallocate their time towards more creative activities, social interactions, and areas where they typically find greater satisfaction and add more value. For instance, journalists might use AI to sift through extensive archives for relevant references, perform spell checks, synthesize pertinent news reports, and translate sources. However, they will continue to write most of the analyses, conduct interviews, and decide which experts to feature, thus enhancing productivity by reducing the time and resource spent on some tasks. Secondly, AI can also complement workers and enhance efficiency even in core tasks. For example, a software developer might use AI tools to generate code, identify bugs, or manage development pipelines, thereby boosting efficiency. Thirdly, AI can accelerate product innovation (Babina et al., 2024) by improving the productivity of R&D, or by automating the production of idea itself (Aghion et al., 2017). Finally, AI can lead to capital deepening by substituting labour with capital, as in previous waves of innovation.

Acemoglu (2024) adapts the task-based framework of Acemoglu and Autor (2011) and Acemoglu and Restrepo (2018, 2020) and proposes a simple formula to evaluate the impact of the first two channels (the automation channel). This formula is a variation of the famous Hulten theorem where the aggregate impact of AI is equal to the product of the GDP share of task that will be impacted by AI over the next 10 years with the average cost saving (or equivalently productivity gains) from automating or completing these tasks with AI. Acemoglu (2024) considers that only 5% of the GDP will be actually impacted by AI over the next 10 years, particularly because many tasks that could be automated are unlikely to be automated due to the very high cost of such a transformation (Svanberg et al., 2024). The average productivity gains on impacted task are estimated at 27% based on microeconomic evidences from several articles (in particular Brynjolfsson et al., 2023). This implies that the expected macroeconomic effects of AI would lead to a modest increase of 0.71% in TFP over a decade, corresponding to an annual TFP growth rate increase of about 0.07%, very far from the impact of previous GPT waves (see Table 1).

Other experts are more optimistic. In its Spring 2024 World Economic Outlook, the IMF forecast a 0.8pp yearly impact of AI on growth (Li and Noureldin, 2024) based on results from Cazzaniga et al. (2024). Using a comparison with previous technological waves, Aghion and Bouverot (2024) also forecasts an effect reaching 0.8pp per year in the next 10 years. Note that these impacts are not limited to the automation channels contrary to Acemoglu (2024)'s estimate, however the latter argues that these alternative channels should not play too high a role in the next ten years. Finally, Aghion and Bunel (2024) conciliates Acemoglu (2024)'s methodology with Aghion and Bouverot (2024) and shows that a cumulative gain of about 7% in the next 10 years from the automation channel can be achieved with reasonable hypothesis on the efficiency gains from AI and the share of tasks that are impacted.

An evaluation for European countries

An appealing feature of Acemoglu (2024)'s approach is that it requires only minimal data to estimate the aggregate impact of AI on TFP, through the automation channel. More precisely, the aggregate effect if equal to the product of four components: (1) Share of GDP accounted for by exposed tasks, (2) Share of these tasks for which it is cost-effective to use AI (3) Average saving cost from AI adoption and (4) the labour share.

We use this formula to provide several estimations of the effect by European country. The first and fourth components are the one that naturally differ across countries. In particular, the distribution of employment across occupations will pin down the first component as we will assume that a given occupation is equally exposed in all countries. We also provide alternative estimates of the average increase in productivity from adopting AI on relevant task and on the share of tasks for which it is cost-effective to use AI based to gauge the range of credible effect that we would expect.

Exposed task and share of GDP

With the rapid advancement of generative AI, it has become increasingly clear that this technology could significantly influence a wide range of occupations, including those in creative sectors and complex, non-routine tasks previously considered immune to automation (Autor, 2015). Advances in AI capabilities such as image recognition, natural language processing, and predictive analytics have contributed to the emergence of a new generation of robots capable of performing social interactions with humans. Consequently, numerous studies have been conducted to assess the vulnerability of various occupations to AI. For example, Webb (2020) analysed the alignment between job descriptions and AI patent texts, proposing that similarities could indicate a potential risk of automation. Eloundou et al. (2023) examined the impact of the GPT language model, suggesting that an occupation is exposed if the technology can substantially reduce the time required for certain tasks, and reported that such exposed tasks constitute about 20% of GDP. Felten et al. (2021) developed the AI Occupational Exposure (AIOE) indicator, which Pizzinelli et al. (2023) also utilized, measuring exposure based on AI's capabilities with potential levels reaching up to 60% of GDP in some countries. Gmyrek et al. (2023) employed GPT-4 to predict typical tasks in various professions and evaluate their automation potential, reporting exposure levels comparable to those found by Eloundou et al. (2023) and used by Acemoglu (2024).

We have applied the AIOE methodology described by Felten et al. (2021) to each 2-digit ISCO08 occupation.[21] While this measure does not specify a clear threshold for classifying occupations as 'exposed by AI', we adopt the approach of Pizzinelli et al. (2023) by considering an occupation as exposed to AI if its AIOE score exceeds the mean. Alternatively, we assess individual exposure by analysing each of the 16,937 tasks listed in the Bureau of Labor Statistics' O*NET database, version 28.1. Using GPT-4, we estimate an exposure score for each task based on its short description available in ONET and a specific prompt detailed in Table A2 in the Appendix. A task is deemed exposed to AI if it scores above 0.8.[22] We then aggregate these scores at the 2-digit ISCO level based on each task's importance to the occupation. The first methodology indicates an exposure level of 43% in the Euro area, while the second methodology yields 52%, both of which are higher than the values reported by

[21] This is an aggregated level of analysis as 2-digit ISCO08 occupations include broad groups such as "teaching professional (23)" or "Managers (11)". This is unfortunately the most detailed level for which we can have employment by sector and country which are necessary to construct our estimates.

[22] This is an arbitrary choice of course and alternative numbers will yield alternative aggregate effects. We explore alternative values, but we should emphasize at this stage that the goal of this exercise is not so much to give an exact prediction but rather to consider plausible order of magnitude for the TFP gains from the automation channel in the medium run and put this in perspective with measured TFP growth rates in the 20th century as reported in Table 1.

Eloundou et al. (2023), who focused solely on the impact of generative AI, and are more aligned with the findings of Pizzinelli et al. (2023).

Cost-efficient automation

An essential aspect of AI's impact on employment, and consequently on economic growth through the automation channel, concerns not only whether an occupation has tasks susceptible to automation but also whether it is economically viable to automate these tasks. Svanberg et al. (2024) highlight this critical point in the context of computer vision technologies. They argue that the costs associated with implementing, maintaining, training, and upgrading such technologies can be prohibitively high, and in particularly much higher than their labour cost, making it infeasible for most firms, except those large enough to realize economies of scale.

Broadly, several barriers could deter a firm from adopting AI for specific tasks, even if these tasks are highly exposed to automation and could theoretically be performed by AI. For instance, while many basic administrative tasks can be efficiently managed by technologies like ChatGPT at minimal cost, and without significant managerial decisions, the application of such generic AI technologies is often restricted to tasks where errors have minor consequences, and the need for personalization and creativity is low. Conversely, many tasks remain challenging to automate with current technology due to insufficient model precision, which may not meet the required quality standards for products or services. Moreover, training such specialized models could be cost-prohibitive, especially if they are tailored to a limited set of tasks. Thus, in the medium term, we can expect that productivity gains from AI will be confined primarily to tasks that are easier to automate. Acemoglu (2024) estimates that only 23% of tasks that are exposed to automation are feasible to automate with current AI technology, based on the case study by Svanberg et al. (2024) on computer vision and assuming a relatively pessimistic projection of declining technology costs.

We construct an alternative estimate by using the AI Occupational Exposure (AIOE) metric from Felten et al. (2021) with our own exposure scores to identify occupations that are highly exposed to AI and yet contain a significant proportion of tasks that are difficult to automate. Specifically, we consider occupations where more than 50% of tasks have a score lower than 0.75 as having a high exposure based on their characteristics but with many tasks considered challenging to automate. This approach suggests that automating all tasks within these occupations would require multiple specialized models, making it expensive in the medium term. We find that 40% of the occupations in the set of those exposed fit this description, which broadly corresponds to Svanberg et al. (2024)'s alternative projection in the case of a 20% annual cost decline in the cost of computer vision technology.[23]

[23] A 20% annual decline in cost may appear extreme, but it is, in fact, not uncommon within the context of computing costs in machine learning (Thompson et al., 2020). Note also that this number of 40% has been calculated at the 4-digit ISCO level to improve the precision.

Labour cost saving (or productivity)

Several studies have sought to quantify the efficiency gains derived from the adoption of AI in exposed tasks. This is notably evident in high-skilled professions such as developers, consultants, and analysts, as well as in roles requiring less education, like customer support positions. For tasks amenable to AI, significant productivity enhancements have been reported. For instance, Noy and Zhang (2023) observed a 40% increase in efficiency for analysts, while Peng et al. (2023) noted a 56% improvement for developers using Copilot. Additionally, AI has been shown to enhance analytical skills—Schoenegger et al. (2024) documented a 23% increase in prediction accuracy in a forecasting tournament—and to boost creativity, as demonstrated by Doshi et al. (2023).

However, these productivity gains are not uniformly distributed across all workers. Dell'Acqua et al. (2023) highlighted that significant gains are primarily realized in tasks where AI has a comparative advantage. Workers using AI indiscriminately across various tasks without strategic integration into their workflow tended to show lesser productivity improvements. Furthermore, Brynjolfson et al. (2023) found that, in contrast to earlier technological adoptions, initially less productive workers tend to benefit more substantially from AI, experiencing greater productivity gains.

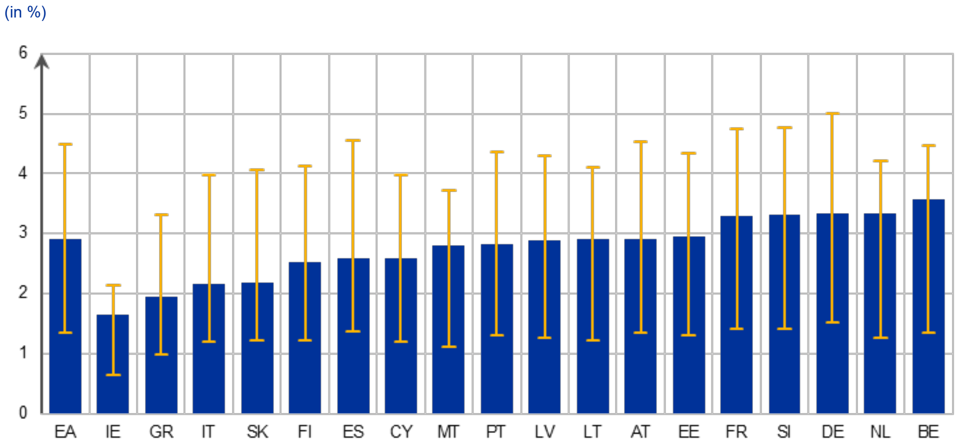
Acemoglu (2024) adopts an average value of 27%, derived from the findings of Brynjolfson et al. (2023) and Peng et al. (2023), to estimate these effects. Notably, Brynjolfson et al. (2023) also indicated that the productivity effect of AI adoption grows over time as workers become more adept at leveraging AI capabilities, with long-term effects being approximately twice as significant as short-term impacts. Based on this, we adopt a central estimate of 35% for our analyses.

Results

To conclude, we measure the labour share in 2022 in the national account. We predict TFP gains of 2.9% in the medium run (say in the next ten years) in the euro area, equivalent to an additional 0.29 percentage points per year. This projection is derived by multiplying the following factors: 0.43 (GDP share of exposed tasks), 0.4 (share of tasks that can be automated among these exposed tasks), 0.35 (efficiency gains on these tasks), and 0.48 (the labour share). These estimates significantly surpass Acemoglu (2024)’s forecast of a 0.7pp gain over the same period, yet remain largely below the annual TFP impacts of ICT in the US, estimated at 0.8pp by Aghion and Bouverot (2024).They are nevertheless insufficient to restore GDP growth to its 20th-century average (see Table 1). Alternative estimates will make this 10-year predicted impact range between 1.3 and 4.5%. Chart 15 reports the effect of individual euro area countries.

Chart 15

Estimated TFP gains in the next 10 years from AI



Sources: Author’s calculation based on Acemoglu (2024).
Notes: Bars present the central scenario of total TFP gains from AI through the automation channel by adapting Acemoglu (2024)’s model to European countries. This scenario uses a threshold of 0.8 to defined exposed tasks, considers that 40% of exposed tasks can indeed be feasibly automated and assumes a 35% higher productivity in these tasks. Lower bounds use respectively 0.85, 0.23 and 27% and upper bounds use 0.75, 0.45 and 40%.

These estimates, while indicative, are surrounded by considerable uncertainty. The projected productivity gains from the automation channel in the medium term are inherently limited by the relatively modest share of tasks that are both exposed to AI and cost-effective to automate. Moreover, these figures should be regarded as preliminary due to several missing dimensions in the analysis. Firstly, the GDP share attributed to occupations and industries most exposed to AI will likely evolve as AI adoption progresses. Secondly, predicting the future development of AI capabilities and associated implementation costs is challenging. Lastly, there are practical limits to how effectively workers can reallocate their time to more creative and valuable tasks, constrained by their capacity to focus on complex tasks continuously. These factors suggest that while automation may drive significant changes, the extent of these changes remains highly uncertain.

Additional (long-run) channels

More importantly, these numbers do not take into account two important channels. On the one hand, if AI can impact the generation of new idea and improve the productivity of R&D which could alleviate the trends in how harder good ideas are to find over time. Jones (2023b) offers a useful framework for understanding the impact of AI on growth through Weitzman (1998)’s recombinant growth model. In this model, growth stems from the generation of new ideas, which are themselves combinations of existing ideas. The primary limitation to growth is the capacity of a finite (but growing) number of researchers to study an exponentially increasing set of ideas and assess their relevance. The integration of AI could mitigate this bottleneck. AI excels at combining existing “recipes” (i.e., generative AI “creates” by blending information learned from a wealth of existing inputs) and could accelerate the pace at which we evaluate these combinations by either dismissing irrelevant combinations or identifying pertinent ones in areas researchers might not consider.

The potential for growth through the integration of AI in generating new ideas and enhancing R&D productivity could be significant as AI could lead to the development of new products or even solve major challenges such as the generation and storage of clean energy. However, these advantages must be weighed against the limitations highlighted by the digital revolution, where technology rents could diminish innovation incentives among the most efficient firms, leading to suboptimal investments in innovation. For instance, Aghion et al. (2023b) illustrate how the declining cost of IT in the 1990s disproportionately benefited the most efficient firms by reducing the resources needed to manage their vast number of production units. Initially, this led to increased innovation and expansion, but ultimately it reduced competition and had negative effects on growth and welfare. Similarly, De Ridder (2024) discusses how the nature of intangibles increased fixed production costs, a phenomenon that could recur with AI if competition policies do not adapt.

4.3 Environmental transition

Climate change is leading to rising temperatures and an increase in adverse extreme events such as flooding, which pose significant risks to the economy and the stability of the financial system. Without substantial mitigation measures, all aspects of the production function—labour, capital, and TFP—will suffer adverse impacts. Moreover, even robust measures to accelerate the transition to cleaner energy may not completely prevent some of these effects from materializing.

Transitioning to sustainable energy sources and environmentally friendly production and consumption practices is arguably one of the greatest challenges facing humanity. It requires substantial investments from both the private and public sectors to alter the environmental footprint of our consumption and firms' production processes. For instance, the European Commission estimates that annual energy investments in the EU will need to reach €396 billion from 2021 to 2030, and €520-575 billion per year through 2050, to achieve the goal of climate neutrality in energy production.

Ambitious public policies like the European Green Deal, which plans around 600 billion euros in investments to significantly reduce carbon emission without harming economic growth or increasing inequality, are already underway. However, to achieve these objectives and limit global warming to levels that will not severely impact the economy and society at large, firms must also enhance their capacity to adopt greener technologies. In this section, we first review the literature on the negative impacts of climate change on growth and productivity. We then discuss how a transition towards green innovation may generate positive externalities and spur growth, provided that institutions are adapted to support the development of green technologies.

4.3.1 The impact of climate change on productivity

The direct impact of climate change on the economy is predominantly negative. Physical risks posed by extreme weather events such as storms, flooding, wildfires, and rising temperatures are expected to adversely affect TFP, capital stock, and labour supply, thereby exerting large and potentially non-linear impacts on both GDP levels and growth rates (Burke et al., 2015; Dell et al., 2012). Bijnens et al. (2024) provide a comprehensive summary of these impacts. Concerning the stock of capital, climate change is projected to increase the capital depreciation rate, shortening the average lifespan of capital assets due to more frequent damage and escalating global uncertainty, which diminishes investment incentives. Bilal and Rossi-Hansberg (2023) analyse these effects within a general equilibrium framework, illustrating that an increase in global temperatures could be interpreted as an elevation in the U.S. capital depreciation rate, with pronounced local impacts—specifically, a potential 2 to 4 percentage point increase per 1°C rise in global mean temperatures along the South-Eastern Atlantic coast.

Regarding labour inputs, higher temperatures and pollution levels may exacerbate mortality rates and chronic illnesses, reducing the available labour supply for tasks incompatible with extreme weather conditions. This spatial heterogeneity in climate impacts is likely to spur significant migration waves, further exacerbating local skill shortages (Leduc and Wilson, 2024). Additionally, TFP is affected as heatwaves and adverse weather conditions can diminish individual worker efficiency. Bijnens et al. (2024) suggest that in countries with an average annual temperature of 25°C, labour productivity could decline by 0.4 percentage points for each additional degree Celsius, reflecting a complex interaction of reduced investment and disruptions in global value chains.

4.3.2 Transition to greener economy and productivity

Without mitigation measures, the impact of climate change on productivity will be severe. However, policies promoting environmental transitions could also independently influence productivity. On one hand, the introduction of more standards and regulations increases uncertainty and risks, making some capital assets obsolete and stranded. This compels firms, governments, and individuals to shift their investments from polluting or energy-inefficient capital towards newer, cleaner technologies. Yet, the productivity gains from such investments may not be immediately evident. Additionally, these regulations can impose production constraints and prompt firms to adopt less efficient processes in the short term. On the other hand, in the longer-run, massive public investments into green innovation can generate positive spillovers to firms even in fields that are not directly linked to energy, just like what was observed with the impact of similar innovation policies during World War Two and the Cold War in the US (see section 3.2.3). While green innovation itself may not solve all the problems of climate change and may face technological bottlenecks, it may have the advantage of mitigating the negative impacts environmental transitions on climate change. Without surprise, how to design the right policies to enhance green innovation, or low-carbon innovation has received considerable attention in the institutional and academic literature (Cervantes et al., 2023).

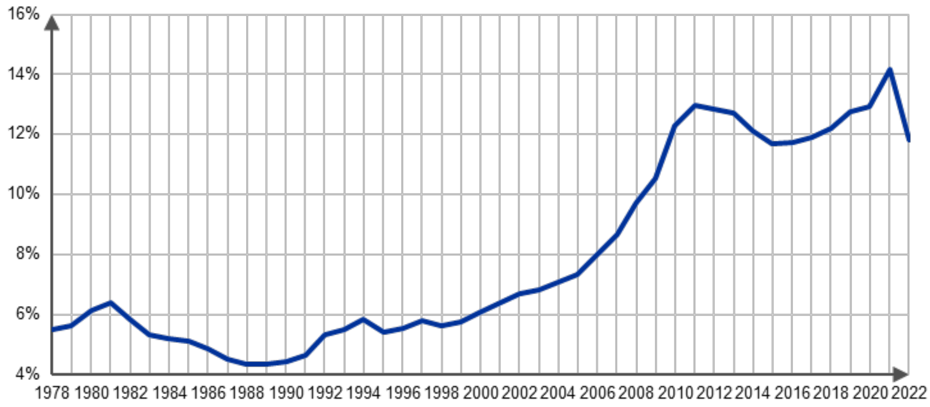
Measuring green innovation can be naturally done with patent data. The OECD offers a classification of patents into green and non-green technologies based on their technological class (Haščič and Migotto, 2015). Aghion et al. (2024) applied this classification to patents in many different countries and report a consistent pattern also shown in Chart 16 for European patents: the green intensity of newly issued patents has plateaued after the Great Financial Crisis, at a level between 10% and 15% depending on the countries. They link this pattern to the path dependency of firms from their innovation history. As noted by Acemoglu et al. (2012), this path dependence grants established firms a comparative advantage in technologies they are familiar with, often those that rely on fossil fuels or polluting activities. Therefore, companies that have historically innovated in such “dirty” technologies are likely to persist in this direction, continuing to develop and enhance these technologies even as new, cleaner options may emerge. More generally, the pervasive uncertainty associated with the environmental transition often makes established firms reluctant to move away from their polluting activities. As Aghion et al. (2016) note, transitioning to a clean economy can be exceedingly slow without public intervention due to path dependence in firms' innovation strategies. Firms with a history of success in polluting industries, such as those in the mid-tech manufacturing sectors prevalent in Europe—like large appliance and automotive manufacturers (see Section 3.2)—tend to stick with familiar technologies.

For this reason, young firms play an important role in fostering green innovation as they are not encumbered by the same path dependencies and may possess a comparative advantage in developing green technologies. However, this also means that green innovation, primarily driven by young firms, is vulnerable to financial difficulties because these firms often face considerable financial constraints. Young firms lack established transaction histories and track records, which raises the costs for banks to monitor them and leads to limited access to bank financing. Furthermore, these firms usually cannot tap into bond or equity markets, restricting their ability to find financial alternatives to bank loans.

Chart 16

Share of green patents

(% of total)



Sources: Aghion et al. (2024)
Notes: Only patents from the European Patent Office are included. A patent is defined as green if it has at least one technological class matching the list presented in Haščič and Migotto (2015).

Aghion et al., (2024) explores this story with a quantitative growth model and find that find that the tightening of credit for young firms after 2010 can explain around 60% of the recent slowdown in the rise of green patenting.

Green patents are special in several respects. By employing the methodology of Haščič and Migotto (2015), we demonstrate in Table 7 that green patents filed at the EPO generally generate significantly more citations and are of higher value according to various quality composite indicators defined by Squicciarini et al. (2013). More notably, these patents also exhibit higher generality and originality indices on average, suggesting that green innovation often relies on the integration of diverse, previously unrelated technologies and tends to inspire follow-up applications across a broader spectrum of technological fields. Consequently, green patents are more likely to catalyse the generation of new ideas across various domains. These findings hold true, conditional on the technological class and the year of application (see Table 7).

Table 7

Green patents and quality indicators

	Forward Citations	Quality Indicator (OECD)	Generality	Originality
Green patent	0.353	0.016	0.039	0.044
	(0.0408)	(0.0014)	(0.0144)	(0.0131)
Average value	0.978	0.314	0.351	0.675

Sources: Author's calculation based on Haščič and Migotto (2015)'s methodology and Squicciarini et al. (2013).
Notes: OLS estimation of a model where the dependent variable is given as a column name and the regressor is a dummy variable equal to 1 is a patent is labelled as green. All patents from the EPO for which we could retrieve an entry in Squicciarini et al. (2013) are included, number of observations: 2,249,577. All models include a technological class-filing year fixed effects where the technological class is the NBER technological class in 35 broad groups. Standard errors are clustered at the technological class level.

The stagnation in the development of green patents, despite significant public and private investments—a trend similarly observed in other countries as highlighted by Aghion et al. (2024)—raises concerns about the ability of these investments to produce substantial positive spillovers to other productivity-enhancing technologies.

Although individual green patents may possess this potential, the broader impact remains limited. This situation underscores the need for substantial changes in the policy mix to break the path dependency of large polluting firms and lower financial barriers for emerging innovators in green technology. Without such reforms, the anticipated benefits may fail to materialize.

5 Policy Implications and Conclusion

Before concluding, we summarize the policy implications of this article.

Strengthening Coordination Among European Countries. Innovation policy in Europe has suffered and continues to suffer from a lack of coordination among European countries, which is necessary to maximize the benefits of innovation and technology adoption. This is particularly crucial in the wake of a new technology revolution. Europe has not fully capitalized on its assets, notably the size of its single market and the quality of its basic sciences, to develop digital giants since the 1990s. Therefore, it is paramount to better coordinate innovation policies across member countries to foster a unified strategy that will avoid the fragmentation of R&D efforts, promote the integration of several key sectors, and intensify the collaboration between university-driven scientific discoveries and the private sector. This enhanced coordination is the condition for a successful industrial policy that could boost overall productivity from investing in the green and AI transition.[24]

Rethink the allocation of R&D subsidies and focus on mission-oriented projects. To escape the middle technology trap and foster innovation that leads to substantial productivity gains, Europe needs to rethink its allocation of R&D subsidies. Current investments tend to favour established sectors like automotive and mechanical engineering, while high-tech sectors such as biotechnology and ICT remain underfunded. By reallocating subsidies towards mission-oriented projects that target high-potential sectors, and by integrating public and private research efforts more effectively, Europe can stimulate breakthrough innovations and catch-up with China and the US without increasing its public R&D expenditures. This strategy can be further strengthened by building around its leadership in green technology. The continent has the potential to lead the world in sustainable innovations, which are crucial for addressing global environmental challenges and can generate significant productivity gains and spillover to the whole economy. However, to fully realize this potential, it is essential to remove barriers that young firms face in accessing external finance. This includes improving venture capital availability and creating supportive regulatory frameworks that encourage investment in green startups.

Enhancing the Adoption and Generation of AI Technologies. To fully harness the potential of AI, policies must encourage not only the use of AI tools but also the

[24] The recent Letta report (Letta, 2024) accordingly stresses that the single market remains a remarkable catalyst for growth but needs to be adapted and accelerate its integration around the green and digital transition.

development of AI innovations within Europe. This includes investing in AI education and training to build a skilled workforce capable of leveraging AI technologies. Additionally, fostering an environment that supports AI startups and encouraging venture capital investment are crucial steps. AI can significantly boost productivity by automating routine tasks and enhancing R&D efficiency through the generation of new ideas and innovations. However, these benefits will only be realized if there is a coordinated effort to integrate AI into existing production processes and ensure that the workforce is equipped to work alongside these new technologies.

Transforming the Labour Market after the Covid-19. The transformation of labour markets following the 2020's pandemic, highlights the need for adaptable and resilient workforce policies. The crisis has accelerated the shift towards remote work, automation, and the gig economy, fundamentally altering traditional labour market dynamics. Policies should focus on supporting workers through these transitions by enhancing social safety nets, providing reskilling and upskilling opportunities, and promoting flexible work arrangements. Ensuring that labour market regulations adapt to new forms of employment is crucial.

Focusing on Europe's comparative advantages. European countries are moving away from the technological frontier after missing the ICT revolution in the 1990s and lagging behind in the production of digital innovations and biotechnologies. However, Europe has many assets that should be leveraged more effectively. First, it has a large market and a rich, educated population whose savings should be redirected towards financing innovation, particularly for young firms, through a more integrated capital market. Second, Europe has a strong capability to generate important ideas and crucial knowledge that has been the foundation of significant innovations developed elsewhere. Strengthening the link between universities and firms and redirecting public R&D expenditures towards riskier, long-term projects would help capitalize on this pool of scientific excellence. Third, Europe holds a relatively leading position in producing green innovations[25] and reducing CO2 emissions. To maintain this position in the future, it is essential to support young firms in financing their R&D projects.

Conclusion

This paper has explored the broad spectrum of European productivity, spanning from the end of the 19th century to its historical peaks in the mid-20th century, through present-day challenges, and into a promising yet uncertain future. This long-term view highlights the remarkable growth of the post-WW2 era while also allowing appreciation of the relative and progressive decline initiated after the 1970s. We documented how this trend can be related to inadequate industrial and innovation policies that suffered from a lack of coordination across countries, inadequate incentives for collaboration with the university ecosystem, and a financial system that does not adequately support risk-taking and the development of rapidly growing startups poised to become leaders in new technological waves.

[25] Europe as a whole (including the UK and Switzerland) has more PCT patent families in green technologies than any other region in the world in 2022.

As a result, the gap with the US has been particularly marked since 1995, raising significant concerns about the future of European economic growth, especially considering that the European innovation landscape continues to suffer from the same issues that contributed to its relative slowdown after the oil crisis. The future of European productivity could hinge on the effective adoption of Artificial Intelligence and climate-related innovations. These technologies hold significant potential to drive productivity gains and could reverse this negative trend. However, we show that the gains from substituting easy-to-automate tasks with AI are relatively modest. To realize the full potential of AI, Europe must encourage firms to invest in developing new models that will improve the quality of goods and services, create new ideas, and solve complex problems. Similarly, we show that the development of green innovation, mostly driven by young firms, has halted since the Great Financial Crisis due to credit constraints. Deriving significant gains from these technological revolutions will thus require better-targeted policy interventions that ensure a better allocation of resources and foster an environment that supports radical technological adoption and development.

The paper also examines post-pandemic trends and the dramatic accelerating relative decline of the euro area compared to the US in terms of labour productivity. Understanding the underlying factors behind this dynamics is particularly crucial for public policy and for monetary policy in particular, namely whether this results from deep structural factors or is a transitory phase exacerbated by multiple shocks. We argue that this accelerating decline is largely driven by transitory factors and will likely be largely reversed in the near future. However, structural factors negatively impacting European productivity for several decades and the threat of a more global period of secular stagnation, particularly resulting from decreasing returns of education, demographic shifts, and growing inequality, raise questions about the ability of European countries to fully bounce back from these major shocks.

Historically, Europe has shown remarkable resilience and an ability for technological and economic transformation, especially in the post-World War II period and at a time when the continent was clearly lagging behind the US. By capitalizing on its comparative advantage and its lead in green technology, Europe has a unique chance to fully embrace the fourth industrial revolution and to restore potential output at a higher level.

References

Acemoglu, D. (2024). The Simple Macroeconomics of AI. Unpublished.

Acemoglu, D., Aghion, P., Bursztyn, L., & Hemous, D. (2012). The environment and directed technical change. American economic review, 102(1), 131-166.

Acemoglu, D., & Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. American economic review, 108(6), 1488-1542.

Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. Journal of political economy, 128(6), 2188-2244.

Acemoglu, D., & Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. In Handbook of labor economics (Vol. 4, pp. 1043-1171). Elsevier.

Aghion, P., Bergeaud, A., De Ridder, M., & Van Reenen, J. (2024). Lost in transition: Financial barriers to green growth.

Aghion, P., Akcigit, U., & Howitt, P. (2014). What do we learn from Schumpeterian growth theory? In Handbook of economic growth (Vol. 2, pp. 515-563). Elsevier.

Aghion, L., Howitt, P., & Levine, R. (2018). Financial development and innovation-led growth. In Handbook of finance and development (pp. 3-30). Edward Elgar Publishing.

Aghion, P., Jones, B. F., & Jones, C. I. (2017). Artificial intelligence and economic growth (Vol. 23928). Cambridge, MA: National Bureau of Economic Research.

Aghion, P., Dechezleprêtre, A., Hemous, D., Martin, R., & Van Reenen, J. (2016). Carbon taxes, path dependency, and directed technical change: Evidence from the auto industry. Journal of Political Economy, 124(1), 1-51.

Aghion, P., Bergeaud, A., Gigout, T., Lequien, M., & Melitz, M. (2023a). Exporting ideas: Knowledge flows from expanding trade in goods. CEP Discussion Paper #1960.

Aghion, P., Bergeaud, A., Boppart, T., Klenow, P. J., & Li, H. (2023b). A theory of falling growth and rising rents. Review of Economic Studies, 90(6), 2675-2702.

Aghion, P., Bergeaud, A., Boppart, T., Klenow, P., & Li, H. (2024). Good rents versus bad rents: R&D misallocation and growth.

Aghion, P. & Bouverot, A. (2024) Commission de l'intelligence artificielle, "IA : Notre ambition pour la France," Technical Report 2024.

Aghion P. & Bunel, S. (2024) AI and Growth: where do we stand? Mimeo LSE.

Aksoy, C. G., Barrero, J. M., Bloom, N., Davis, S. J., Dolls, M., & Zarate, P. (2022). Working from home around the world (No. w30446). National Bureau of Economic Research.

Andrews, D., Nicoletti, G., & Timiliotis, C. (2018). Digital technology diffusion: A matter of capabilities, incentives or both?

Andrews, D., Criscuolo, C., & Gal, P. N. (2016). The best versus the rest: the global productivity slowdown, divergence across firms and the role of public policy.

Arce, O., Consolo, A., Dias da Silva, A. & Mohr, M. (2023) More jobs but fewer working hours. ECB Blog 7 June 2023.

Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. Journal of economic perspectives, 29(3), 3-30.

Autor, D., & Salomons, A. (2017). Does productivity growth threaten employment. In ECB Forum on Central Banking, Sintra, Portugal (pp. 26-28).

Azoulay, P., Graff Zivin, J. S., Li, D., & Sampat, B. N. (2019a). Public R&D investments and private-sector patenting: evidence from NIH funding rules. The Review of economic studies, 86(1), 117-152.

Azoulay, P., Fuchs, E., Goldstein, A. P., & Kearney, M. (2019b). Funding breakthrough research: promises and challenges of the "ARPA Model". Innovation policy and the economy, 19(1), 69-96.

Babina, T., Fedyk, A., He, A., & Hodson, J. (2024). Artificial intelligence, firm growth, and product innovation. Journal of Financial Economics, 151, 103745.

Baffigi, A. (2011). Italian national accounts, 1861-2011. Bank of Italy Economic History Working Paper, (18).

Baldwin, R., & Teulings, C. (2014). Secular stagnation: facts, causes and cures. London: Centre for Economic Policy Research-CEPR.

Barrero, J. M., Bloom, N., Buckman, S., & Davis, S. (2024). SWAA April 2024 Updates. Work from Home Research.

Barrero, J. M., Bloom, N., & Davis, S. J. (2020). 60 million fewer commuting hours per day: How Americans use time saved by working from home. University of Chicago, Becker Friedman Institute for Economics Working Paper, (2020-132).

Barrero, J. M., Bloom, N., Davis, S. J., & Meyer, B. H. (2021a, COVID-19 is a persistent reallocation shock. In AEA Papers and Proceedings (Vol. 111, pp. 287-291). 2014 Broadway, Suite 305, Nashville, TN 37203: American Economic Association.

Barrero, J. M., Bloom, N., & Davis, S. J. (2021b). Let me work from home, or I will find another job. University of Chicago, Becker Friedman Institute for Economics Working Paper, (2021-87).

Barrero, J. M., Bloom, N., & Davis, S. J. (2023). The evolution of work from home. Journal of Economic Perspectives, 37(4), 23-49.

Barro, R. J., & Ursúa, J. F. (2008). Macroeconomic crises since 1870 (No. w13940). National Bureau of Economic Research.

Barsky, R. B., & Kilian, L. (2002). Oil and the macroeconomy since the 1970s. Journal of Economic Perspectives, 18(4), 115-134.

Baruffaldi, S., van Beuzekom, B., Dernis, H., Harhoff, D., Rao, N., Rosenfeld, D., & Squicciarini, M. (2020). Identifying and measuring developments in artificial intelligence: Making the impossible possible.

Bergeaud, A., & Verluise, C. (2024). A new dataset to study a century of innovation in Europe and in the US. Research Policy, 53(1), 104903.

Bergeaud, A., & Verluise, C. (2023). Identifying technology clusters based on automated patent landscaping. Plos one, 18(12), e0295587.

Bergeaud, A., Guillouzouic, A., Henry, E., & Malgouyres, C. (2022b). From public labs to private firms: magnitude and channels of R&D spillovers.

Bergeaud, A, Gozen, R. and Van Reenen, J. (2023) Mapping International Technological Trajectories: Evidence from Multiple Patent Offices over Four Centuries. Mimeo LSE.

Bergeaud, A., & Lepetit, M. (2020). RESEARCH PROGRAM CH. DUPIN.

Bergeaud, A., & Ray, S. (2020). The macroeconomics of teleworking. Economic research, 231, 2.

Bergeaud, A., Cette, G., & Stary, J. (2022a). Recruitment Difficulties and Firms' Characteristics: An Analysis of French Company Data. Economie et Statistique/Economics and Statistics, (534-35), 43-59.

Bergeaud, A., Cette, G., & Drapala, S. (2023). Telework and Productivity Before, During and After the COVID-19 Crisis. Economie et Statistique/Economics and Statistics, 539, 73-89.

Bergeaud, A., Cette, G., & Lecat, R. (2016). Productivity trends in advanced countries between 1890 and 2012. Review of Income and Wealth, 62(3), 420-444.

Bergeaud, A., Cette, G., & Lecat, R. (2017). Total factor productivity in advanced countries: A long-term perspective. International Productivity Monitor, (32), 6.

Bianchini, N. & Ancona, L. (2023) Artificial intelligence: Europe needs to start dreaming again. Schuman Papers n°728.

Bilal, A., & Rossi-Hansberg, E. (2023). Anticipating climate change across the United States (No. w31323). National Bureau of Economic Research w31323.

Bijnens, G., Anyfantaki, S., Colciago, A., De Mulder, J., Falck, E., Labhard, V., Lopez-Garcia, P., Lourenço, N., Meriküll, J., Parker, M., Röhe, O., Schroth, J., Schulte, P. & Strobel, J. (2024). The impact of climate change and policies on productivity. ECB Occasional Paper, (2024/340).

Blanchard, O. (2002). The economic future of Europe. Journal of Economic Perspectives, 18(4), 3-26.

Bloom, N., & Van Reenen, J. (2007). Measuring and explaining management practices across firms and countries. The quarterly journal of Economics, 122(4), 1351-1408.

Bloom, N., Sadun, R., & Reenen, J. V. (2012). Americans do IT better: US multinationals and the productivity miracle. American Economic Review, 102(1), 167-201.

Bloom, N., Liang, J., Roberts, J., & Ying, Z. J. (2015). Does working from home work? Evidence from a Chinese experiment. The Quarterly journal of economics, 130(1), 165-218.

Bloom, N., Van Reenen, J., & Williams, H. (2019). A toolkit of policies to promote innovation. Journal of economic perspectives, 33(3), 163-184.

Bloom, N., Jones, C. I., Van Reenen, J., & Webb, M. (2020). Are ideas getting harder to find? American Economic Review, 110(4), 1104-1144.

Bloom, N., Bunn, P., Mizen, P., Smietanka, P., & Thwaites, G. (2023). The impact of COVID-19 on productivity. Review of Economics and Statistics, 1-45.

Bontadini, F., Corrado, C., Haskel, J., Iommi, M., & Jona-Lasinio, C. (2023). EUKLEMS & INTANProd: industry productivity accounts with intangibles. Sources of growth and productivity trends: methods and main measurement challenges, Luiss Lab of European Economics, Rome.

Bresnahan, T. F., & Malerba, F. (1997). Industrial dynamics and the evolution of firms' and nations' competitive capabilities in the world computer industry. CESPRI.

Bundesbank (2024). Development in euro area business dynamism. Monthly Report – March 2024.

Brynjolfsson, E., Rock, D., & Syverson, C. (2021). The productivity J-curve: How intangibles complement general purpose technologies. American Economic Journal: Macroeconomics, 13(1), 333-372.

Brynjolfsson, E., Li, D., & Raymond, L. R. (2023). Generative AI at work (No. w31161). National Bureau of Economic Research.

Burke, M., Hsiang, S. M., & Miguel, E. (2015). Global non-linear effect of temperature on economic production. Nature, 527(7577), 235-239.

Cazzaniga, M., Jaumotte, F., Li, L., Melina, G., Panton, A. J., Pizzinelli, C., Rockall, E. & Tavares, M. M. (2024). Gen-AI: Artificial Intelligence and the Future of Work. Staff Discussion Notes, 2024(001).

Cervantes, M., Criscuolo, C., Dechezleprêtre, A., & Pilat, D. (2023). Driving low-carbon innovations for climate neutrality.

Cette, G., Devillard, A., & Spiezia, V. (2022). Growth factors in developed countries: A 1960–2019 growth accounting decomposition. Comparative Economic Studies, 1-27.

Cette, G., Drapala, S., & Lopez, J. (2023). The circular relationship between productivity and hours worked: A long-term analysis. Comparative Economic Studies, 65(4), 650-664.

Cohen, A. J., & Harcourt, G. C. (2003). Retrospectives whatever happened to the Cambridge capital theory controversies? Journal of Economic Perspectives, 17(1), 199-214.

Criscuolo, C., Gal, P., Leidecker, T., Losma, F., & Nicoletti, G. (2023). Les liens entre télétravail et productivité pendant et après la pandémie de Covid-19/The Role of Telework for Productivity During and Post COVID-19. Economie et Statistique, 539(1), 53-75.

Criscuolo, C. (2021). Productivity and Business Dynamics through the lens of COVID-19: the shock, risks and opportunities. Beyond the pandemic: the future of monetary policy, 117.

David, P. A. (1990). The dynamo and the computer: an historical perspective on the modern productivity paradox. The American Economic Review, 80(2), 355-361.

Delgado, M., Porter, M. E., & Stern, S. (2010). Clusters and entrepreneurship. Journal of economic geography, 10(4), 495-518.

Dell, M., Jones, B. F., & Olken, B. A. (2012). Temperature shocks and economic growth: Evidence from the last half century. American Economic Journal: Macroeconomics, 4(3), 66-95.

Dell'Acqua, F., McFowland, E., Mollick, E. R., Lifshitz-Assaf, H., Kellogg, K., Rajendran, S., Krayer, L., Candelon, F. & Lakhani, K. R. (2023). Navigating the jagged technological frontier: Field experimental evidence of the effects of AI on knowledge worker productivity and quality. Harvard Business School Technology & Operations Mgt. Unit Working Paper, (24-013).

Demirer, M., Hernández, D. J. J., Li, D., & Peng, S. (2024). Data, Privacy Laws and Firm Production: Evidence from the GDPR (No. w32146). National Bureau of Economic Research.

De Ridder, M. (2024). Market power and innovation in the intangible economy. American Economic Review, 114(1), 199-251.

Devulder, A, Ducoudré, B, Lemoigne, M & Zubert, T (2024). Comment expliquer les pertes de productivité observées en France depuis la période pré-Covid? Bulletin de la Banque de France 251/1.

Dingel, J. I., & Neiman, B. (2020). How many jobs can be done at home? Journal of public economics, 189, 104235.

Doshi, A. R., & Hauser, O. (2023). Generative artificial intelligence enhances creativity. Available at SSRN.

Dyevre, A. (2023). Public R&D spillovers and productivity growth. Working paper.

Eaton, J., & Kortum, S. (1999). International technology diffusion: Theory and measurement. International Economic Review, 40(3), 537-570.

ECB (2020). Financial Integration and Structure in the Euro Area.

Eichengreen, B. J. (1993). Reconstructing Europe's trade and payments: the European Payments Union. University of Michigan Press.

Eichengreen, B. (2006). The European economy since 1945: coordinated capitalism and beyond. Princeton University Press.

Eloundou, T., Manning, S., Mishkin, P., & Rock, D. (2023). Gpts are gpts: An early look at the labor market impact potential of large language models. arXiv preprint arXiv:2303.10130.

Felten, E., Raj, M., & Seamans, R. (2021). Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses. Strategic Management Journal, 42(12), 2195-2217.

Felten, E., Raj, M., & Seamans, R. (2023). How will Language Modelers like ChatGPT Affect Occupations and Industries? arXiv preprint arXiv:2303.01157.

Ferguson Jr, R. W., & Wascher, W. L. (2004). Distinguished lecture on economics in Government: lessons from past productivity booms. Journal of Economic Perspectives, 18(2), 3-28.

Fernald, J. G., Inklaar, R., & Ruzic, D. (2023, February). The productivity slowdown in advanced economies: common shocks or common trends? Federal Reserve Bank of San Francisco.

Fernald, J. G. (2015). Productivity and Potential Output before, during, and after the Great Recession. NBER macroeconomics annual, 29(1), 1-51.

Fuest, C., Gros, D., Mengel, P., Presidente, G. and Tirole, J. (2024) How to Escape the Middle Technology Trap A Report by the European Policy Analysis Group.

Gal, P., Nicoletti, G., von Rüden, C., Sorbe, S., & Renault, T. (2019). Digitalization and productivity: in search of the holy grail-firm-level empirical evidence from European countries. International Productivity Monitor, 37(Fall), 39-71.

Galor, O. (2005). From stagnation to growth: unified growth theory. Handbook of economic growth, 1, 171-293.

Garcia-Macia, D. (2017). The financing of ideas and the great deviation (No. 2017/176). International Monetary Fund.

Gayer, C., Reuter, A., Thum-Thysen, A., & Verwey, M. (2024) Vulnerabilities of the labour market: A new survey-based measure of labour hoarding in the EU. VoxEu Column (7 Mar 2024).

Gmyrek, P., Berg, J., & Bescond, D. (2023). Generative AI and Jobs: A global analysis of potential effects on job quantity and quality. ILO Working Paper, 96.

Goldin, I., Koutroumpis, P., Lafond, F., & Winkler, J. (2024). Why is productivity slowing down? Journal of Economic Literature, 62(1), 196-268.

Gordon, R. J. (1999). US economic growth since 1870: one big wave? American Economic Review, 89(2), 123-128.

Gordon, R. J. (2012). Is US economic growth over? Faltering innovation confronts the six headwinds (No. w18315). National Bureau of Economic Research.

Gordon, R. (2017). The rise and fall of American growth: The US standard of living since the civil war. Princeton university press.Gordon, R. J., & Sayed, H. (2019). The industry anatomy of the transatlantic productivity growth slowdown (No. w25703). National Bureau of Economic Research.

Griliches, Z. (1998). Patent statistics as economic indicators: a survey. In R&D and productivity: the econometric evidence (pp. 287-343). University of Chicago Press.

Gross, D. P., & Sampat, B. N. (2023). America, jump-started: World War II R&D and the takeoff of the US innovation system. American Economic Review, 113(12), 3323-3356.

Guerini, M., Nesta, L., Ragot, X., & Schiavo, S. (2024). Zombification of the economy? Assessing the effectiveness of French government support during COVID-19 lockdown. Journal of Economic Behavior & Organization, 218, 263-280.

Haščič, I., & Migotto, M. (2015). Measuring environmental innovation using patent data.

Hall, B. H., & Lerner, J. (2010). The financing of R&D and innovation. In Handbook of the Economics of Innovation (Vol. 1, pp. 609-639). North-Holland.

Hamilton, J. D. (1983). Oil and the macroeconomy since World War II. Journal of political economy, 91(2), 228-248.

Hausman, N. (2022). University innovation and local economic growth. Review of Economics and Statistics, 104(4), 718-735.

Herrigel, G. (1997). Industrial constructions: The sources of German industrial power (Vol. 9). Cambridge University Press.

Hu, A. G., & Jefferson, G. H. (2009). A great wall of patents: What is behind China's recent patent explosion? Journal of Development Economics, 90(1), 57-68.

IEA (1982) World Energy Outlook 1982, International Energy Agency, Paris.

Jones, C. I. (2002). Sources of US economic growth in a world of ideas. American economic review, 92(1), 220-239.

Jones, C. I. (2023a). The Outlook for Long-Term Economic Growth (No. w31648). National Bureau of Economic Research.

Jones, C. I. (2023b). Recipes and economic growth: A combinatorial march down an exponential tail. Journal of Political Economy, 131(8), 1994-2031.

Jorgenson, D. W. (1984). The role of energy in productivity growth. The Energy Journal, 5(3), 11-26.

Jorgenson, D. W. (2001). Information technology and the US economy. American Economic Review, 91(1), 1-32.

Kantor, S., & Whalley, A. T. (2023). Moonshot: Public R&D and growth (No. w31471). National Bureau of Economic Research.

Kelly, B., Papanikolaou, D., Seru, A., & Taddy, M. (2021). Measuring technological innovation over the long run. American Economic Review: Insights, 3(3), 303-320.

Kiszewski, A. E., Cleary, E. G., Jackson, M. J., & Ledley, F. D. (2021). NIH funding for vaccine readiness before the COVID-19 pandemic. Vaccine, 39(17), 2458-2466.

Lalinsky, T., Anastasatou, M., Anyfantaki, S., Benkovskis, K., Bergeaud, A., Bun, M., and cohautors (2024). The impact of the COVID-19 pandemic and policy support on productivity.

Leduc, S., & Wilson, D. J. (2023, July). Climate Change and the Geography of the US Economy. Federal Reserve Bank of San Francisco.

LeMoigne, M. (2020). Exploring the ‘Fissured workplace’: Internal job ladders’ fragmentation and its effect on plants and workers. Working Paper.

Lesterquy, P., Stojanovic, E., Dekoninck, H. & Zory, J. (2024) Baisse de la productivité du travail dans l’industrie en France en 2023: un constat et des leviers d’action. Bulletin de la Banque de France #251/2.

Letta, E. (2024). Much More Than a Market-Speed, Security, Solidarity: Empowering the Single Market to deliver a sustainable future and prosperity for all EU Citizens.

Li, N & Noureldin, D. (2024) World Must Prioritize Productivity Reforms to Revive Medium-Term Growth. IMF Blog, April 2024.

Lopez-Garcia, P., and Szörfi, B. (2021). “Key factors behind productivity trends in euro area countries”. Economic Bulletin Articles, 7/2021.

Maddison, A. (2006). The world economy. OECD publishing.

Madsen, J. B. (2010). The anatomy of growth in the OECD since 1870. Journal of Monetary Economics, 57(6), 753-767.

Marx, M., & Fuegi, A. (2020). Reliance on science: Worldwide front-page patent citations to scientific articles. Strategic Management Journal, 41(9), 1572-1594.

Marx, M., & Fuegi, A. (2022). Reliance on science by inventors: Hybrid extraction of in-text patent-to-article citations. Journal of Economics & Management Strategy, 31(2), 369-392.

Maslej, N., Fattorini, L., Perrault, R., Parli, V., Reuel, A., Brynjolfsson, E., Etchemendy, J., Ligett, K., Lyons, T., Manyika, J., Niebles, J.C., Shoham, Y., Wald, R. & Clark, J. (2024) “The AI Index 2024 Annual Report,” AI Index Steering Committee, Institute for Human-Centered AI, Stanford University, Stanford, CA, April 2024.

Melitz, M. J., & Polanec, S. (2015). Dynamic Olley-Pakes productivity decomposition with entry and exit. The Rand journal of economics, 46(2), 362-375.

Mohnen, P., & Hoareau, C. (2003). What type of enterprise forges close links with universities and government labs? Evidence from CIS 2. Managerial and decision economics, 24(2-3), 133-145.

Nordhaus, W. D. (1996). Do real-output and real-wage measures capture reality? The history of lighting suggests not. In The economics of new goods (pp. 27-70). University of Chicago Press.

Noy, S., & Zhang, W. (2023). Experimental evidence on the productivity effects of generative artificial intelligence. Science, 381(6654), 187-192.

OECD (2016). Economic Policy Reforms 2016-Going for Growth Interim Report. OECD Publishing.

OECD (2019), Going Digital: Shaping Policies, Improving Lives, OECD Publishing, Paris.

Owen, G. (2012). Industrial policy in Europe since the Second World War: what has been learnt? (No. 1/2012). ECIPE occasional paper.

Peng, S., Kalliamvakou, E., Cihon, P., & Demirer, M. (2023). The impact of ai on developer productivity: Evidence from github copilot. arXiv preprint arXiv:2302.06590.

Philippon, T. (2019). The great reversal: How America gave up on free markets. Harvard University Press.

Pizzinelli, C., Panton, A., Mendes Tavares, M., Cazzaniga, M., & Li, L. (2023). Labor Market Exposure to AI: Cross-country Differences and Distributional Implications.

Prados De La Escosura, L. (2003). El progreso económico de España: 1850-2000. Fundación BBVA (Madrid).

Prescott, E. C. (2004). Why do Americans work so much more than Europeans? NBER working paper #10316.

Rachel, L. (2022). Leisure-enhancing technological change. Mimeo, London School of Economics.

Schivardi, F., & Schmitz, T. (2020). The IT revolution and southern Europe’s two lost decades. Journal of the European Economic Association, 18(5), 2441-2486.

Schnabel, I. (2024) “From laggard to leader? Closing the euro area’s technology gap”. Inaugural lecture of the EMU Lab 16 February 2024.

Schoenegger, P., Park, P. S., Karger, E., & Tetlock, P. E. (2024). AI-Augmented Predictions: LLM Assistants Improve Human Forecasting Accuracy. arXiv preprint arXiv:2402.07862.

Schurr, S. H., & Netschert, B. C. (1960). Energy in the American economy, 1850-1975. John Hopkins Press.

Schurr, S. H. (1982). Energy efficiency and productive efficiency: some thoughts based on American experience. The Energy Journal, 3(3), 3-14.

Servan-Schreiber, J. J. (1967). Le défi américain. DeNoel, Paris.

Smil, V. (2010) Energy Transitions: History, Requirements, Prospects.

Smits, J. P., Horlings, E., & Van Zanden, J. L. (2000). Dutch GNP and its components, 1800-1913.

Squicciarini, M. P., & Voigtländer, N. (2015). Human capital and industrialization: Evidence from the age of enlightenment. The Quarterly Journal of Economics, 130(4), 1825-1883.

Squicciarini, M., Dernis, H., & Criscuolo, C. (2013). Measuring patent quality: Indicators of technological and economic value. OECD Publishing.

Strauss, D, Fleming, S., Romei, V. and Arnold, V. (2024) “Europe faces ‘competitiveness crisis’ as US widens productivity gap”. Financial Times March 9 2024.

Svanberg, M., Li, W, Fleming, M., Goehring, B. & Thompson, N. (2024). Beyond AI Exposure: Which Tasks are Cost-Effective to Automate with Computer Vision? Working paper FutureTech MIT.

Thompson, N. C., Greenewald, K., Lee, K., & Manso, G. F. (2020). The computational limits of deep learning. arXiv preprint arXiv:2007.05558.

Valero, A., & Van Reenen, J. (2019). The economic impact of universities: Evidence from across the globe. Economics of Education Review, 68, 53-67.

Verluise, C. & De Rassenfosse, G. (2020) PatCit: A Comprehensive Dataset of Patent Citations. Available in Zenodo (doi 10.5281/zenodo.3710994).

Weitzman, M. L. (1998). Recombinant growth. The Quarterly Journal of Economics, 113(2), 331-360.

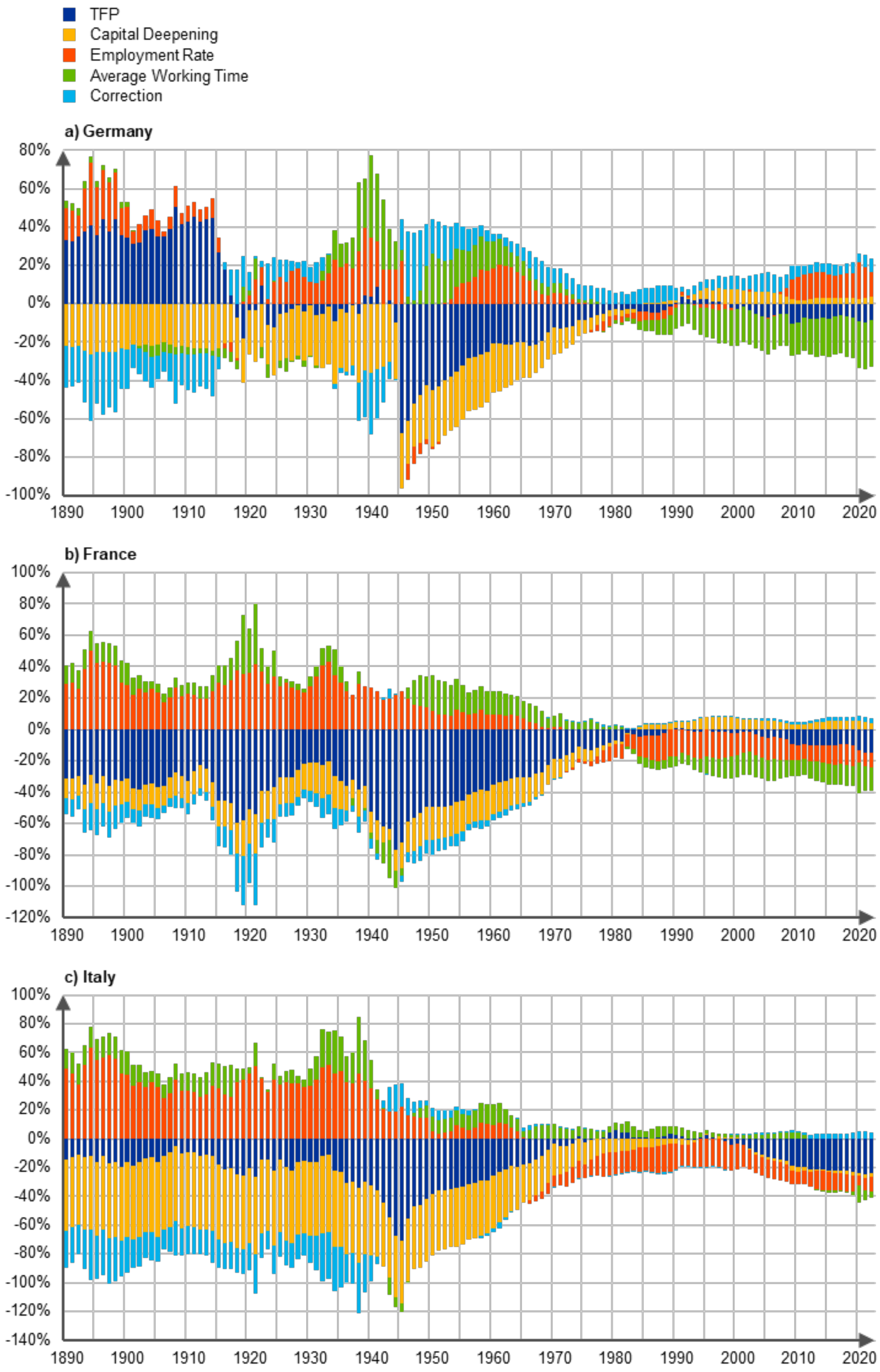
Yergin, D. (2011). The prize: The epic quest for oil, money & power. Simon and Schuster.

Appendix

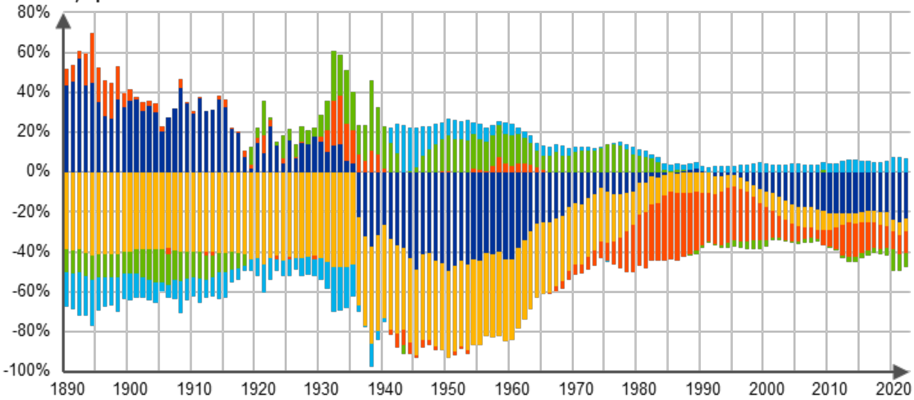
Chart A1

Growth accounting – comparison with the US

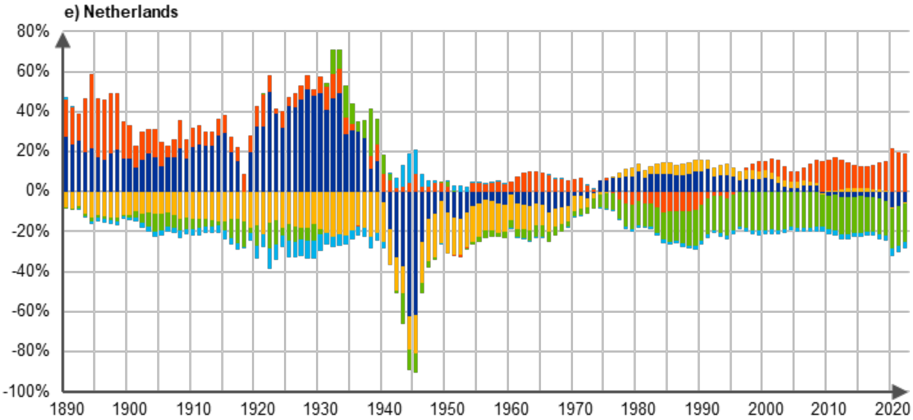
(in %)



d) Spain



e) Netherlands



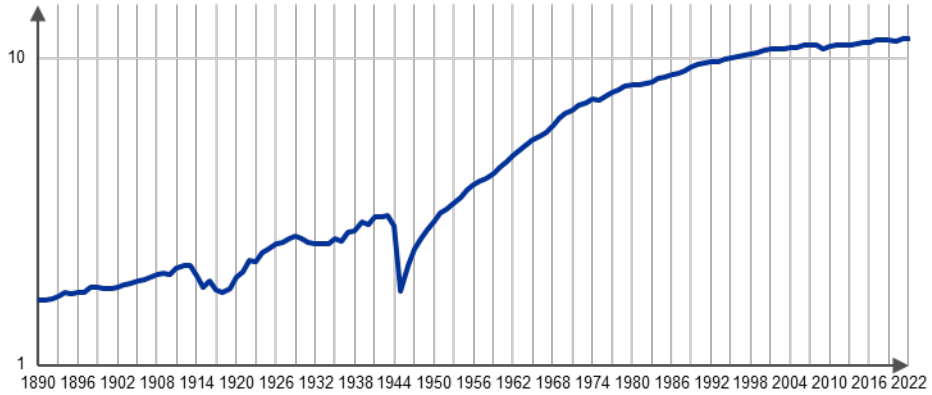
Sources: Long Term Productivity Project (Bergeaud et al., 2016, updated from here).
Notes: These charts replicate Chart 2b for Germany, France, Italy, Spain and Netherlands.

Chart A2

TFP in the euro area 1890-2022

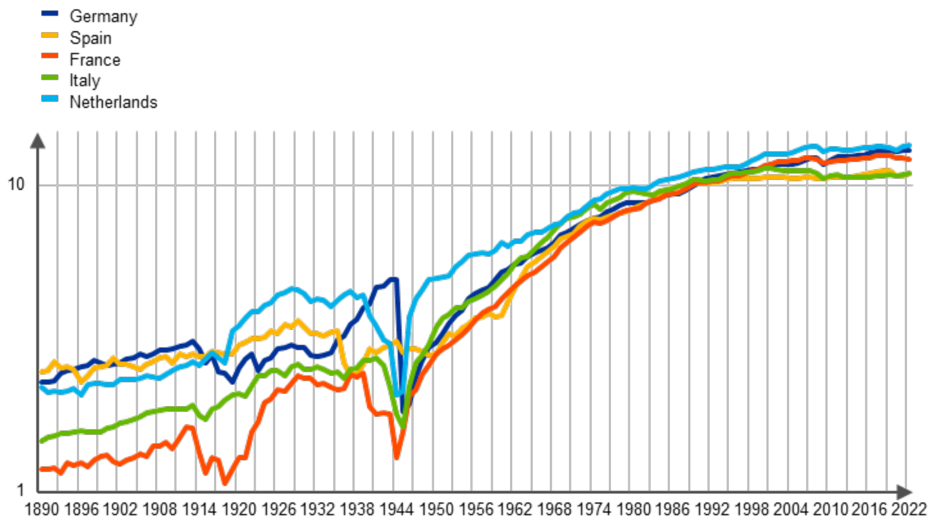
a) TFP in the Euro area

(logarithmic scale)



b) TFP in 5 countries

(logarithmic scale)

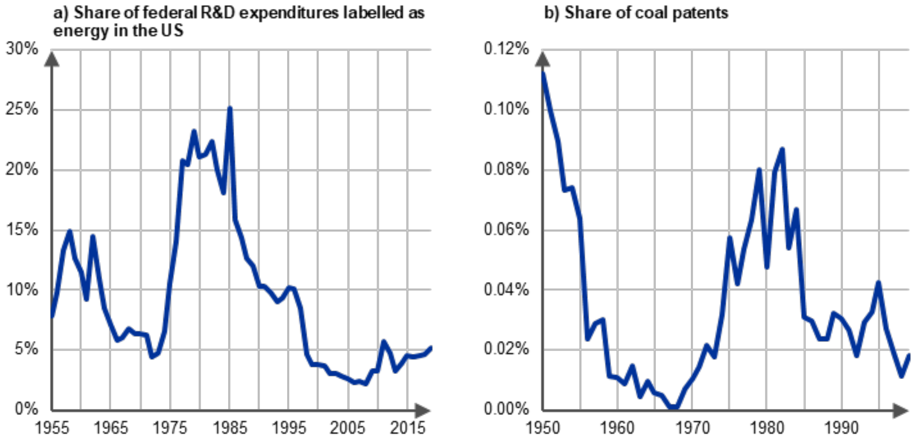


Sources: Long Term Productivity Project (Bergeaud et al., 2016, updated from here).
Notes: TFP is defined as a Solow residuals from dividing the level of GDP in constant US dollars of 2015 by a weighted geometrical mean of total hours worked and the physical stock of capital.

Chart A3

Federal fundings in Energy and Patenting in Coal

(%)

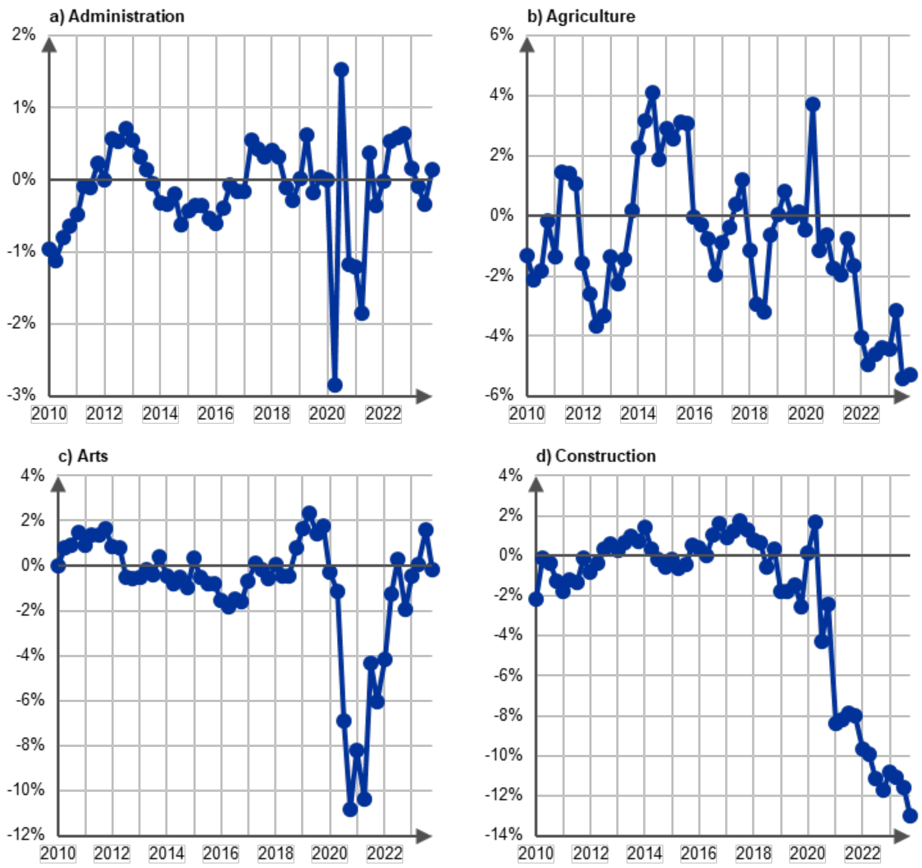


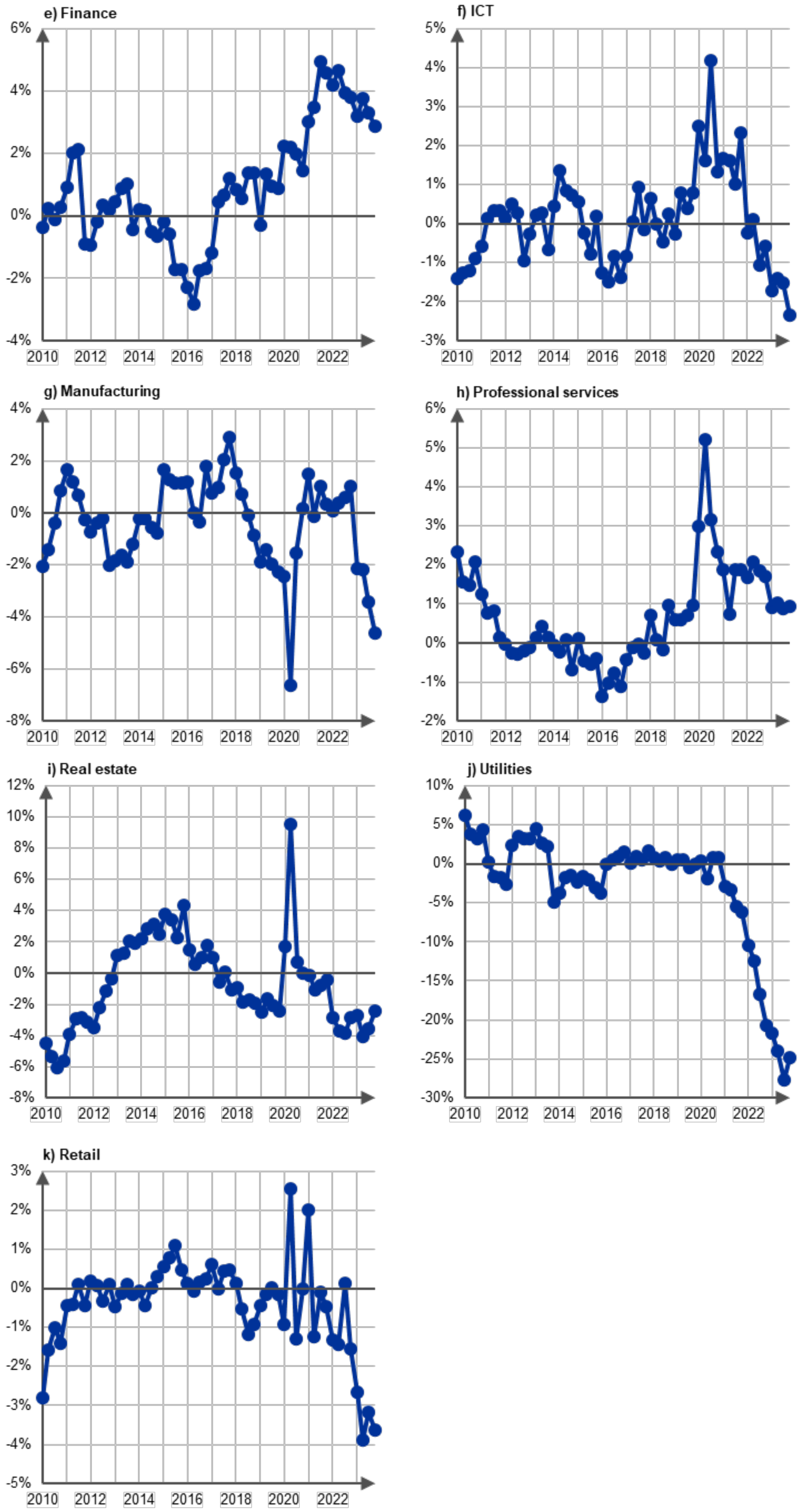
Sources: Dyèvre (2024) for chart A3a and Google Patent Public Dataset for chart A3b
Notes: Chart A3a reports the composition of outlays for the conduct of R&D labelled as energy over the total excluding defence and is originated from the White House Historical Table. Chart A3b plots the share of patents with an IPC code starting with C10J3: “Production of gases containing carbon monoxide and hydrogen”.

Chart A4

Labour productivity and deviation from trend by sector

(in %)





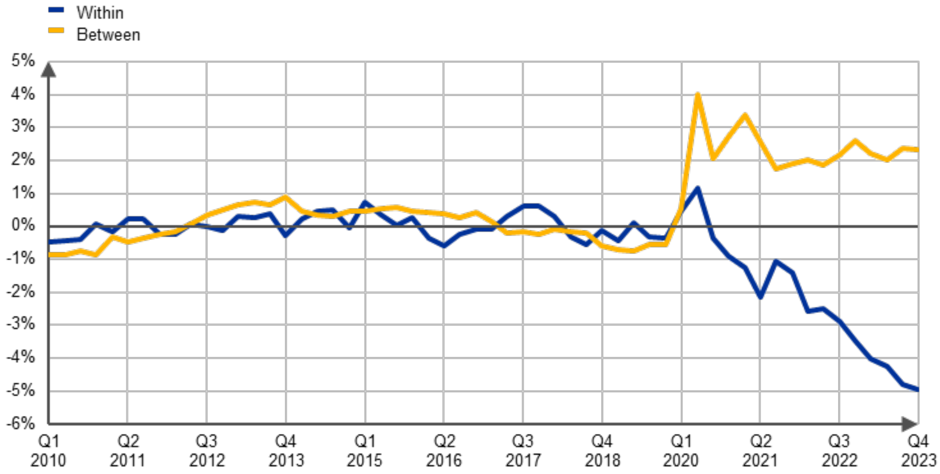
e) Finance
6%
4%
2%
0%
-2%
-4%
2010 2012 2014 2016 2018 2020 2022
f) ICT
5%
4%
3%
2%
1%
0%
-1%
-2%
-3%
2010 2012 2014 2016 2018 2020 2022
g) Manufacturing
4%
2%
0%
-2%
-4%
-6%
-8%
2010 2012 2014 2016 2018 2020 2022
h) Professional services
6%
5%
4%
3%
2%
1%
0%
-1%
-2%
2010 2012 2014 2016 2018 2020 2022
i) Real estate
12%
10%
8%
6%
4%
2%
0%
-2%
-4%
-6%
-8%
2010 2012 2014 2016 2018 2020 2022
j) Utilities
10%
5%
0%
-5%
-10%
-15%
-20%
-25%
-30%
2010 2012 2014 2016 2018 2020 2022
k) Retail
3%
2%
1%
0%
-1%
-2%
-3%
-4%
-5%
2010 2012 2014 2016 2018 2020 2022

Sources: Eurostat Quarterly National Accounts.
Notes: These graphs replicate Chart7b separately for each sector presented in Table 3.

Chart A5

Within-Between decomposition of labour productivity in the euro area

(in %)

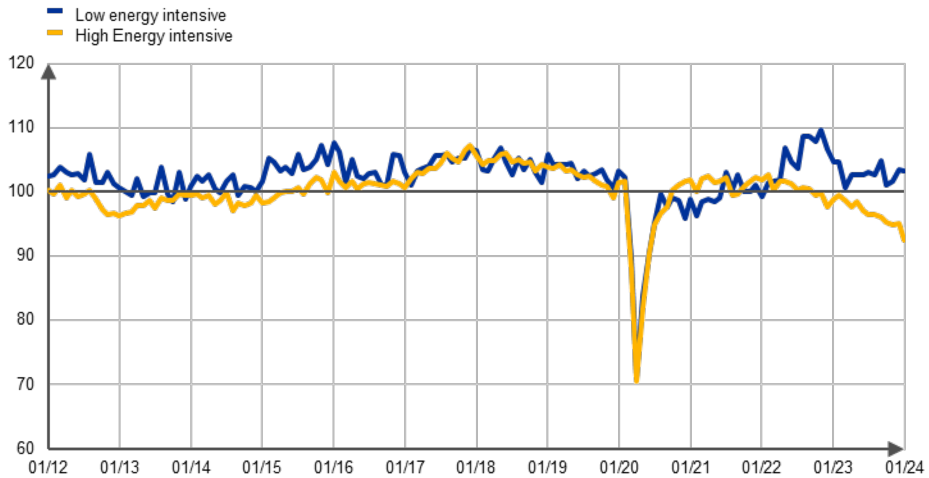


Sources: Eurostat Quarterly National Accounts
Notes: Decomposition of labour productivity into a within component and a between component following the Olley and Pakes (1996) decomposition presented in equation (3). Each of the two terms are taken in logarithm and residualised on their 2010q1-2019q4 trend.

Chart A6

Monthly production and energy intensity

(index (2015 = 100))

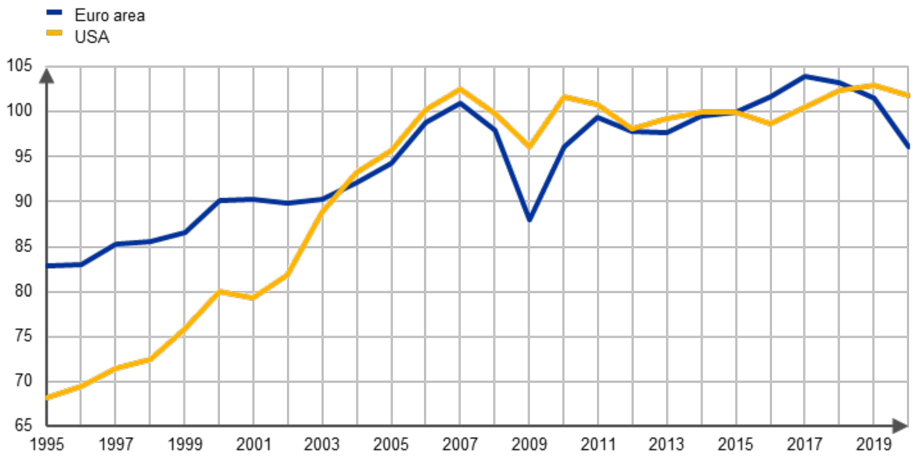


Sources: Eurostat short-term indicator and Eurostat energy statistics
Notes: 24 2-digit manufacturing sectors are split into 2 groups of equal size based on their consumption of electricity and heat in 2019 divided by their value added. For the two groups, we calculate the unweighted average index of production every month.

Chart A7

TFP in the manufacturing sector

(index, 2015 = 100)

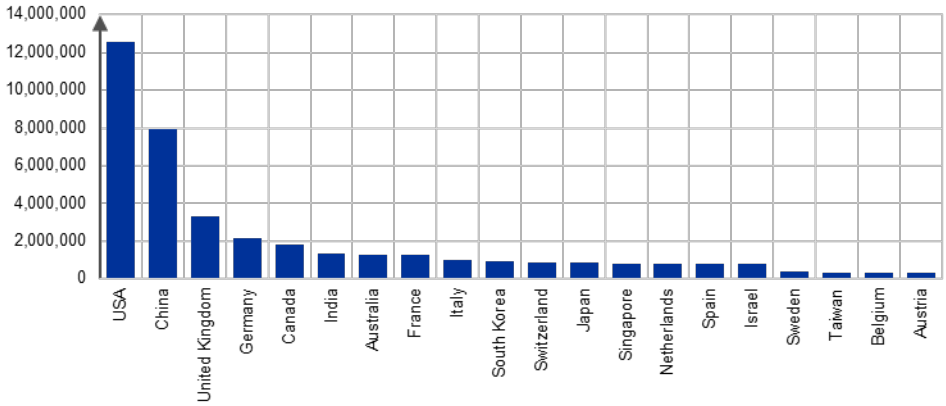


Sources: EU Klems
Notes: Index of TFP in the euro area is calculated by aggregating Germany, France, Italy, Spain, the Netherlands, Austria and Finland using nominal value added weights.

Chart A8

Number of AI academic papers weighted by citations by origin of the authors

(index, 2015 = 100)



Sources: Country Activity Tracker of the Emerging Technology Observatory (March 2024's version)
Notes: Number of papers published in AI since 2013, weighted by citation received as of 2024. The allocation of authors is based on their affiliation at the time the paper was published.

Table A1

Top 10 most AI cited papers

Rank	Title	Affiliations
1	Deep Residual Learning for Image Recognition	Microsoft Research
2	Adam: A Method for Stochastic Optimization	University of Amsterdam, OpenAI
3	Very Deep Convolutional Networks for Large-Scale Image Recognition	University of Oxford
4	Attention is All You Need	Google, University of Toronto
5	BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding	Google
6	Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks	Microsoft, University of Sciences and Technology of Hefei (China)
7	Going Deeper with Convolutions	Google, University of North Carolina, University of Michigan
8	Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift	Google
9	Fully convolutional networks for semantic segmentation	UC Berkeley
10	Dropout: a simple way to prevent neural networks from overfitting	University of Toronto

Sources: Country Activity Tracker of the Emerging Technology Observatory (March 2024's version).
Notes: Affiliation of authors have been retrieved by looking at the first page of each published version.

Table A2

Prompt used for GPT4

Task Assessment

Consider the full range of what Generative AI can currently achieve and what it is projected to do efficiently over a reasonable time horizon. This includes advancements in automation, data analysis, natural language processing, creative generation, and other emerging technologies. Take also into consideration what AI cannot do efficiently and the limitation of other related technologies such as robotics.

Based on AI Capabilities described above, analyse the task '{description}' in the following dimension:

- Substitution Potential: Assess the extent to which AI and generative AI could potentially replace human labour in this task.
- Consider factors like technological feasibility, complexity, ethical considerations, and practical limitations.

Instructions:

- Provide a score ranging from 0 to 1 with 2 decimals. No explanations are required. Only the scores should be given, representing the substitution potential of AI for the task respectively.

Score: