Pro-Productivity Policies for the US Economy

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Abstract

Against the backdrop of slower growth globally, U.S. productivity growth has been faster than many peer economies. We argue that the reasons for U.S. productivity leadership go to both the remarkable engine of innovation represented by public and private sector research and development and to the economic dynamism that promotes the adoption of new technologies, the introduction of new business models, the entry of innovative firms, and reallocation of labor and capital to their best uses. This paper uses the policy scheme proposed by Dirk Pilat and Bart Van Ark to look at the source of growth: factor accumulation, competition policy, support of technology, and policies to support internationalization. We also explore the emerging technology of AI and its likely impact on future growth, the labor market and the distribution of earnings. There is a brief history of U.S. productivity and policy, including the surge of growth in the late 1990s and early 2000s.

Pro-Productivity Policies for the US Economy

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10/30/2025

Abstract

Against the backdrop of slower growth globally, U.S. productivity growth has been faster than many peer economies. We argue that the reasons for U.S. productivity leadership go to both the remarkable engine of innovation represented by public and private sector research and development and to the economic dynamism that promotes the adoption of new technologies, the introduction of new business models, the entry of innovative firms, and reallocation of labor and capital to their best uses. This paper uses the policy scheme proposed by Dirk Pilat and Bart Van Ark to look at the source of growth: factor accumulation, competition policy, support of technology, and policies to support internationalization. We also explore the emerging technology of AI and its likely impact on future growth, the labor market and the distribution of earnings. There is a brief history of U.S. productivity and policy, including the surge of growth in the late 1990s and early 2000s.

I. Introduction

The U.S. economy has the highest labor productivity level among major economies and regions, and its productivity growth is currently matching or outpacing that of most other advanced economies.[2] Moreover, U.S. output per hour has exceeded that of Europe since (at least) the late 19th century.[3] A more critical perspective concerning U.S. productivity shows that since the early 1970s, productivity growth has been slow relative to the previous 100 years; the United States is part of what van Ark, de Vries, and Pilat (2024) call the "leading but slowing" group of countries. Unlike other members of that group, though, the United States saw a surge in output per hour from 1995 to 2004, due primarily to its role in the global information technology (IT) sector. These successes suggest that the U.S. economy may provide information revealing

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[2] The United States leads in gross domestic product per hour in 2021 dollars converted using purchasing power parities from the Total Economy Database published by the Conference Board. Productivity growth rates are from OECD (2024).

[3] See the Long-Term Productivity Database, see: https://longtermproductivity.com. The Europe figure is for the aggregate of countries currently in the European Union.

effective economic policies that have supported this productivity leadership. While nearly all economic policy bears on productivity, which is a primary driver of output, income, and welfare, we focus this paper primarily on policies relevant for the IT sector and the emerging role of artificial intelligence (AI).

We argue that the credit for U.S. productivity leadership goes both to the remarkable engine of innovation represented by public and private sector research and development (R&D) and to the economic dynamism that promotes the adoption of new technologies, the introduction of new business models, the entry of innovative firms, and reallocation of labor and capital to their best uses. Put in terms of growth accounting, growth in total factor productivity (TFP)—the amount of output produced with a given set of inputs—is what distinguishes the U.S. economy from others.[4] The United States is the top national spender on R&D, followed closely by China, with a particular emphasis on IT. Many of the world's leading IT companies are headquartered in the United States and U.S. companies account for two-thirds of all global IT R&D, making the United States a global innovation leader in the sector (Ponciano 2023).[5] Historically, U.S. business dynamism—the reallocation of resources to their most productive use—has been among the highest among advanced economies as well (Haltiwanger et al. 2014). However, dynamism has declined in recent years (Decker et al. 2016). The slow growth of U.S. labor productivity since 1970 has been driven largely by the low growth in total factor productivity (TFP) and there is evidence that this is the result both of a decline in innovation and a decline in dynamism.[6]

From the growth accounting perspective, productivity growth not attributed to TFP comes from capital deepening—more equipment, software, and so forth per worker—and labor quality—more production-relevant knowledge and skills per worker. To a great extent, these investments in physical, intangible, and human capital are the downstream effects of growth in TFP. TFP growth in the manufacturing sector, for instance, typically lowers the cost of investment in

[4] Hulten (2010) is a good entry point for the literature on growth accounting.
[5] U.S.-headquartered companies also account for two-thirds of R&D in the financial services sector and roughly half of R&D in healthcare equipment and services, pharmaceuticals and biotechnology, and aerospace and defense.
[6] Gordon and Sayed (2019) suggest that technological opportunities are drying up. Bloom et al. (2020) and Jones (2009) argue R&D is getting more expensive. However, see Fort et al. (2025) for evidence that there is no secular decline in high-quality patenting. On dynamism, see, for example, Andrews et al. (2016), who show that leading firms continue to push the TFP frontier but laggards cannot keep up, suggesting that new ideas are not being transferred and adopted.

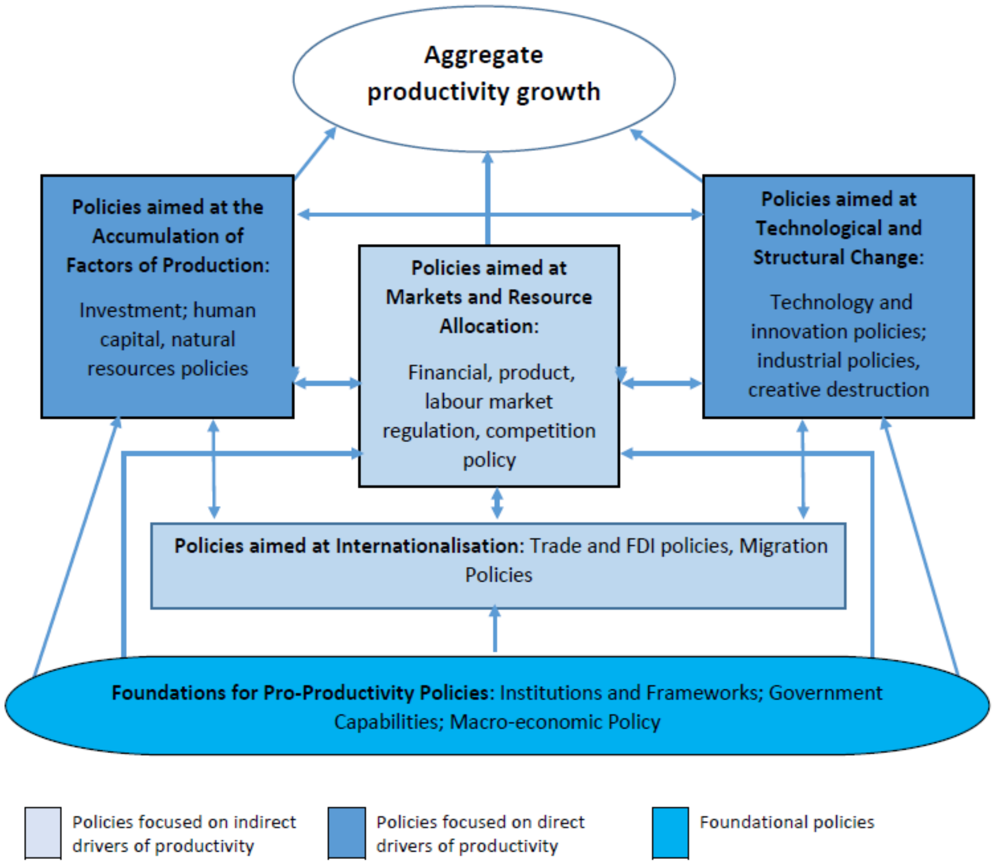
goods, leading to capital deepening. And, when new business models emerge in response to TFP growth, they may shift derived demand for human-embodied capabilities.[7] Even so, TFP alone does not determine capital per worker; policy can affect the responsiveness of capital deepening to TFP-driven incentives as well.

We adopt the comprehensive framework provided by Bart van Ark and Dirk Pilat (Van Ark et al., 2024) to examine growth policies, though we focus on a subset of policy types most relevant for the U.S. experience and for which we have something to contribute (Figure 1). In particular, we discuss factor accumulation, the role of competition policy, policies to enhance technological change and policies directed at internationalization. We also look at the potential impact of AI on the labor market and the earnings distribution.[8]

[7] In recent decades, technology has tended to be skill-biased, driving up demand for human capital, but this need not be the case (Berman et al. 1998).

[8] Our primary focus is on aggregate productivity, but we note that pro-productivity policies should be evaluated for their distributional effects as well. Other things equal, policies that increase the share of income going to wages are desirable in the current environment because productivity gains have not translated into widespread prosperity and the lack of good jobs for workers without higher education and the decline in the labor share of income is one reason for social discontent. Real weekly median earnings for men declined from 1980 through the mid-1990s and, while they have grown since then, they have only recently exceeded their 1980 level. The comparable earnings figures for women show an upward trend, although women still earn less than men. The weakness in male earnings stems from multiple factors, including the decline in manufacturing employment. Meeting these challenges would require policies that can simultaneously enhance productivity and ensure equitable returns to labor.

Figure 1. Pro-Productivity Policy Schema



Source: van Ark, de Vries, and Pilat (2024)

The remainder of the paper is organized as follows. In the next section, we provide a brief history of U.S. productivity and policy, calling out examples of the policy types provided in van Ark, de Vries, and Pilat (2024), hereafter "AVP." Then in the section that follows, we decompose the contours of post-war productivity growth into contributions from TFP, capital deepening, and labor quality. We ask what caused the U.S. productivity slowdown around 1970, the brief surge in 1995-2004, and the return to slow growth since and whether this yields any lessons for policy today. Next, we zero in on AI policy, because if AI develops as some people think it will, it becomes the main source of productivity growth and productivity policy. In the last few years, AI has made explosive progress, providing the potential to sustain or even accelerate productivity growth (although not the certainty of it). In section IV, we describe the broad frameworks for AI regulation adopted by the European Union, the Biden and Trump administrations, and U.S. states. In section V, we offer some high-level thoughts on the policy approaches found in those frameworks and further discuss immigration policy and policies to address disruptions to the labor market as AI is adopted. We conclude with some thoughts on lessons learned from the commonalities of country experiences presented in the companion papers in this Series on Country Experiences of Productivity Policies (https://www.productivity.ac.uk/news/pro-productivity-policies-country-experiences-series/)

II. U.S. Productivity and Policy: A Brief History

Although the focus of this paper is on productivity policy from the 1970s forward, we provide a concise longer history as there is a substantial amount of interesting variation in U.S. pro-productivity policies in earlier periods. We then turn to a deeper look at the past 50 years or so. Broadly speaking, the U.S. experience can be viewed in terms of four eras. Productivity growth picked up from the slow pace that characterized the colonial period with the arrival of the Industrial Revolution and the advent of the Republic.[9] Then, Gordon (2016) identifies circa 1870 as a turning point when U.S. labor productivity growth increased significantly further and remained elevated for roughly 100 years (Figure 3). From around 1970 to the present, labor productivity has been more subdued, except for a revival fueled by information technology in the late 1990s and early 2000s.

From Colonial America to World War II

Early American policy relevant for productivity was more limited than in later eras, but the establishment of the United States was a radical shift. A consistent legal code, currency, and regulation of interstate trade provided an opportunity for Smithian growth through lower "iceberg costs" and a larger market.

The federal government established standards (weights and measures, currency), an example of AVP's institutions and frameworks, and regulated trade through tariffs. The national government intervened in the labor market to a limited degree, a notable example being fugitive slave laws, but relevant social policy, such as rules for labor conditions, was minimal and largely a matter

[9] Maddison (2003) estimates that U.S. GDP per capita rose 0.7 percent per year on average from 1700 to 1820, then stepped up to 1.3 percent for the 1820 to 1870 period. Bergeaud et al. (2016) estimate that GDP per capita rose 2.0 percent per year on average from 1870 to 1970.

for state and local government. Direct government involvement in the economy was present as well. Postal delivery was provided beginning in 1775, which may be viewed as an extreme form of AVP's product market regulation. Policies to support technological change included the establishment of the Patent Office in 1790, followed by continual refinement of patent law to the present day.[10] And, the federal government promoted structural change through the sale of federal lands to railroad developers beginning in the 1850s, which spurred development of farmland and commercial activity in Chicago and other cities. The late 19th century saw an explosion of industrial activity, especially in railroads, coal mining, and large-scale factories. A primary focus of federal government intervention in that period was on competition, particularly in railroads, where the Interstate Commerce Commission endeavored to mitigate price discrimination. Around the turn of the century, as the adverse effects of largely unfettered industrialization became apparent, regulations to provide for basic workplace and product safety were put in place.

Following World War I, government took a more laissez-faire approach to economic policy. David and Wright (1999, 2005) document the rapid growth of productivity in many industries in the 1920s and 1930s, including manufacturing, electricity and rail transportation. Government intervention soared with the New Deal, including safety net policies (Social Security, unemployment insurance), a pro-union orientation (National Labor Relations Act), and direct government involvement in production (Works Progress Administration, Tennessee Valley Authority). Such policies changed how government and industry interact, increasing costs on business through new regulations and programs while aiming to stabilize demand and employment following the aftermath of the Great Depression (Fishback 2017).

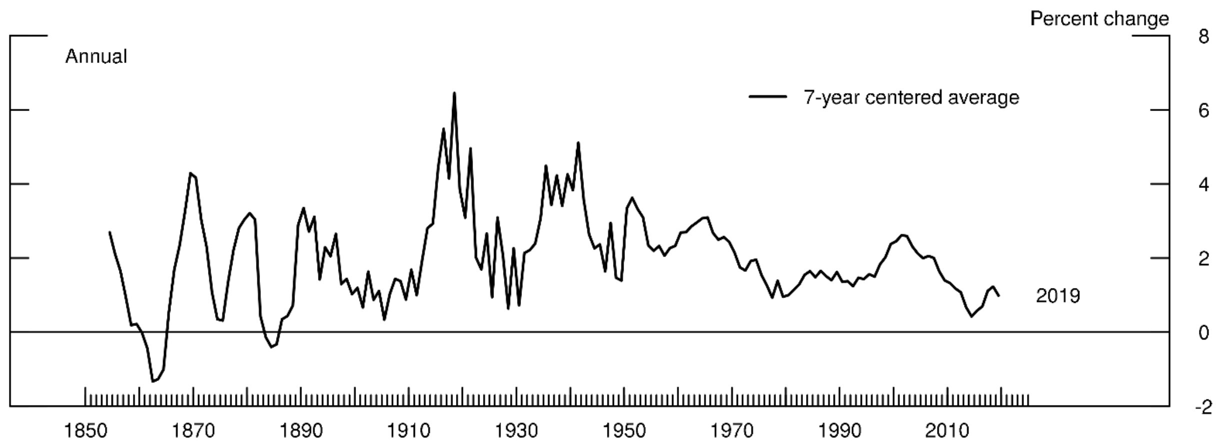
The entry of the United States into World War II brought aggressive government control of the economy as well (price and wage controls, rationing, the War Production Board). Government spending on R&D soared, including grants to universities and establishment of government labs. This research, combined with learning-by-doing during the all-out war effort, triggered productivity advances in military equipment, munitions and war materiel, but also in dual-use technologies such as aircraft, radar, and computing.

[10] See Appendix A for a short history of U.S. Federal innovation policy.

Post-War America before 1970

After the war, there was strong household demand and technologies that had been developed or refined during the war could be applied for civilian production. The economies of Europe and Japan having been shattered by the war, created strong demand for U.S. export goods. International trade was supported by a new global orientation that emerged from the Bretton Woods agreement and the General Agreement on Tariffs and Trade, including the gold standard, which reduced exchange rate volatility, and a push for open markets. As shown in Figure 3, productivity growth for 25 years after the war was very strong.

Figure 3. U.S. Labor Productivity



Note: Total economy productivity.
Source: Long Term Productivity Database. Bergaud, Cette, Lecat (2016).

One of the technologies developed during the war was leading-edge computing. Spurred by the Cold War, the U.S. Department of Defense continued to provide resources to develop computer technology for cryptography and ballistics and provided strong demand for semiconductors and computers for advanced weapons. The resulting innovations were soon deployed for back-office activities at private corporations as well. During this period, there were two poles of IT development in the United States.. On the east coast there were IBM and Digital Equipment Corporation who had become the dominant providers of mainframe computers. However, on the west coast, in Silicon Valley, the industry was developing separately as Hewlett Packard expanded its focus from instruments to computers and Fairchild Semiconductor was founded in 1957.[11] Stanford University also played an important role in the semiconductor industry and

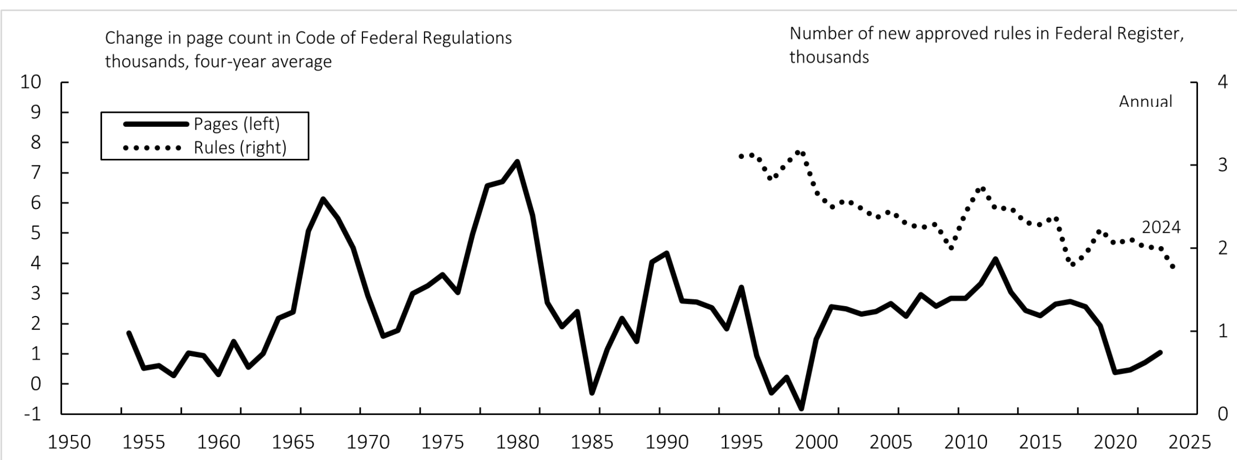
[11] Saxenian (2000) highlights the competition between east and west coast companies.

started the first computer science department in 1965.   Importantly, though, widely used personal computing technology remained rather primitive, relying on human power, slide rules, and mechanical calculators to make many of the calculations needed for solving mathematical and engineering problems.

The launch of Sputnik in 1957 was a big shock to the United States and triggered a burst of government funding and activity to sustain or regain American technological leadership. Scholarships were instituted to encourage students to study science and technology. The National Science Foundation and the National Institute of Standards and Technology (NIST) pre-dated Sputnik but were given more funding after the launch and the Defense Advanced Research Projects Agency (DARPA), the defense research arm, was started in 1958. The National Institutes of Health go back to the early twentieth century but saw greatly increased funding. As well as government support for hardware, there was also support for software technologies.

The complex economic regulatory system that developed during the Great Depression was substantially expanded during the Johnson administration with the Great Society which provided support for education (e.g. Head Start), health care (Medicare and Medicaid), product safety (cigarette labels, motor vehicle safety), and a host of environmental regulations. These and other initiatives served to boost worker productivity through health and human capital but also created a tremendous amount of compliance burden for private business.

Figure 4. The Pace of New U.S. Federal Regulation



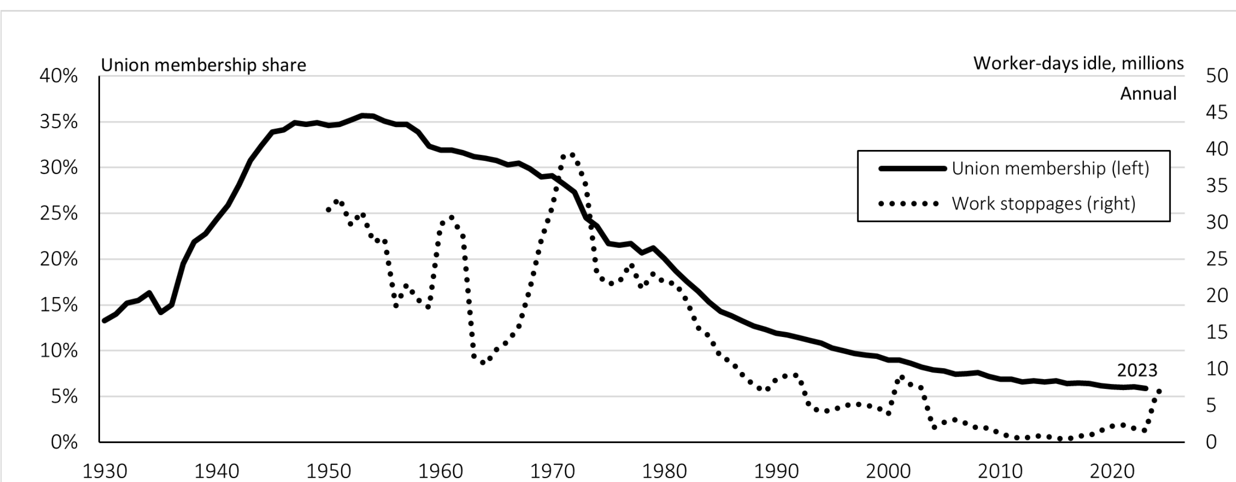
Source: George Washington University Regulatory Studies Center.

From 1970 to the Present

By the early 1970s productivity growth had slowed, there was a jump in inflation, strike activity had spiked, and the zeitgeist began to shift. The Nixon administration was wary of government regulation, in the main, but the U.S. Congress did not share his perspective and continued to push in the other direction, including the creation of the Environmental Protection Agency (Figure 4). Nixon was no free-market purist, however; he experimented with price controls to contain consumer inflation and pressured the Federal Reserve to lower interest rates (Abrams 2006).

The pace of regulation picked back up during the Carter administration, though his administration also began a sweeping effort to deregulate transportation. The accumulation of new regulations, together with the slowdown in productivity growth led to a push for deregulation during the Reagan administration. Reagan also introduced an aggressive program of tax reduction. While the lower tax and regulation environment encouraged investment, the primary budget deficit rose sharply during the 1980s as the tax cuts were not matched with comparably lower spending and monetary policy was sharply restrictive in response to inflation. On net, government policy seemed to restrain productivity growth, which remained weak until the 1990s as discussed in the next section. Meanwhile, the Federal Reserve under Chairman Volcker maintained unprecedented high interest rates to quash inflation, restore the institution's credibility, and build confidence in the fiat money and floating exchange rate regime that followed the exit from the Gold Standard in 1971.

Figure 5. Unionization, Private Sector



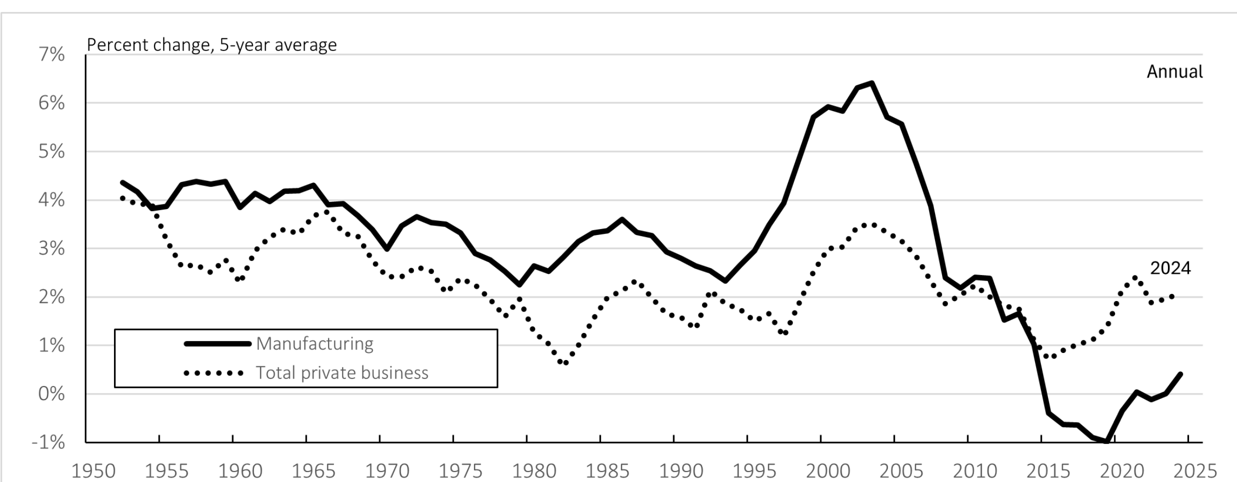
Source: Economic Policy Institute (unionization), extended by data from http://www.unionization.com; Bureau of Labor Statistics (stoppages).

Reagan also signaled the arrival of a new attitude toward unionization by firing over 10,000 striking air traffic controllers and hiring non-union employees. The private sector also pushed against unions by hiring non-union workers and by moving to Southern states where the legal environment was anti-union. While lower unionization allows for more flexible adjustment of labor inputs by business, on net, the drop in unionization may have contributed negatively as empirical evidence suggests a positive impact of unions on productivity in manufacturing and construction (Brown and Medoff 1978; Clark 1984; Allen 1986; DiNardo and Lee 2004; Lee and Mas 2009; Sojourner et al. 2015).

From the Reagan administration forward, the growth in the Code of Federal Regulation was restrained, with a sharp reduction during the "Reinventing Government" initiative under Clinton and the Trump administration's executive order that two regulations must be eliminated with the introduction of each new one. The Dodd-Frank regulations caused a pop after 2010, though the impact was damped by softening of those rules in 2018.

As will be discussed in detail in the next section, productivity and GDP growth strengthened temporarily in the 1990s. Mostly due to the resulting increase in income and capital gains tax receipts, the federal budget was balanced for the first time since the early 1960s. Lower government borrowing led to lower Treasury yields and a more favorable environment for private capital deepening.

Figure 6. Manufacturing Labor Productivity



Note: Manufacturing productivity is Federal Reserve industrial production index divided by BLS production worker hours.

Source: Bureau of Labor Statistics; Federal Reserve Board.

Historically, the manufacturing sector has outpaced the rest of the economy for labor productivity and production worker earnings, so the decline in U.S. manufacturing employment, which took a sharp downturn in the early 2000s, was viewed with alarm. This decline in employment is often referred to as the “China shock” because it coincided with the entry of China into the WTO. Chinese exports to the United States played a role in the manufacturing employment decline, although the drop in domestic demand growth was just as important.[12] Policymakers looked for policies that favor expansion of the sector, including trade policy (both higher tariffs for infant industry protection and lower tariff agreements to promote market access), tax incentives for investment (accelerated depreciation schedules, R&D tax credits), and favoring domestic manufacturers in government procurement. Clinton and Obama favored greater opportunities for workers to train or get educational support, but these programs have had modest impacts. The Clinton administration explicitly justified the negotiation of the North American Free Trade Agreement (NAFTA) with a claim that it would increase U.S. manufacturing jobs. In the wake of NAFTA and China’s accession to the World Trade Organization, politicians viewed the decline by 2.5 million in production workers in the sector with alarm.[13] Domestic manufacturing of electronics was hit particularly hard, leading to initiatives in the Obama and Biden administrations to promote U.S. high tech manufacturing. While support for science and technology programs remained broadly stable, policy shifts and proposed cuts during the Trump Administrations have made the future of federal research support more uncertain.

The Trump Administration has turned aggressively toward tariffs to promote U.S. manufacturing. The ultimate structure of the tariffs is hard to predict at this stage as negotiations with trading partners are ongoing. A direct benefit of tariffs is that they generate tax revenue, which is welcome, given the large US federal budget deficit. However, a cost of tariffs is that they can cause inflation, which may lead the central bank to raise interest rates, slowing the economy (and

[12] Lawrence (2024).
[13] Specifically, the establishment of Permanent Normal Trade Relations (PNTR) as part of China’s accession to the WTO sparked a sharp decline in U.S. manufacturing employment (Pierce and Schott 2014).

damping tax revenue).[14] Moreover, firms are reluctant to reorganize supply chains unless there is certainty about trade policy and current policy uncertainty remains high. The Administration and Congress have also put in place tax cuts that will likely worsen the budget deficit, widening the gap between saving and investment and probably contributing to an increase in the trade deficit.[15]

III. Sources of Post-War Productivity Growth

Labor Productivity Growth from 1948 through 1995. From 1948 through 1973 there was strong labor productivity growth in the business sector of the US economy, equal to 3.34 percent a year (figure 7). Nearly two-thirds of this growth, 2.16 percent a year, is attributable to total factor productivity growth (TFP), according to the Bureau of Labor Statistics (BLS).[16] Capital deepening (increases in the capital labor ratio) accounted for 0.97 percent per year on average, with the final rather small piece coming from improvements in labor composition at 0.18 percent per year.[17]

The golden period of post-war productivity growth in the U.S. 1948-73 was helped by capital accumulation and by the increased education and skills of the workforce. However, it was overwhelmingly the result of TFP growth, that can be described as improvements in technology—producing more output with the same inputs—and economic dynamism—the ability of the economy to shift labor and capital toward their most productive uses as technology changes. Over this period large power plants and steel mills were became much more productive. Small retailers gave way to supermarkets that were more convenient and more productive. Business managers figured out how to run their operations more efficiently, such as reorganizing

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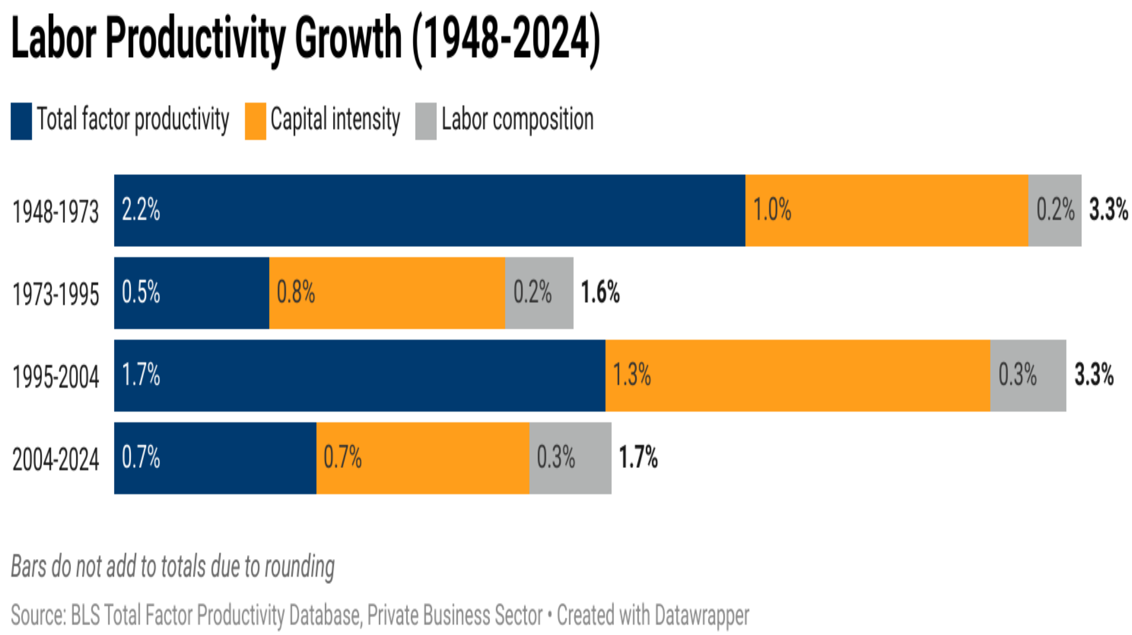
[14] Whether tariffs cause a temporary increase in inflation as prices rise to a new level incorporating the tariff or a sustained increase is a subtle question. Empirically, tariffs have tended to cause temporary increases (Schmitt-Grohé and Uribe 2025), but channels for sustained inflation include higher inflation expectations and lower productivity growth as firms adjust their supply chains to produce in new locations.
[15] There is not a one-to-one relation between the budget deficit and the trade deficit and, if there is a recession, the two deficits will move in opposite directions. Still, a substantial and sustained reduction in the current account deficit would be hard to accomplish without reducing the budget deficit.
[16] Productivity data from the Bureau of Labor Statistics, Office of Productivity and Technology, OPT Data, https://www.bls.gov/productivity/data.htm The note on labor composition is found at: Productivity Measures, Calculation, subhead on Labor Input, https://www.bls.gov/opub/hom/msp/calculation.htm
[17] In the labor contribution, BLS uses "age, gender, and education levels as proxies for experience and ability." Importantly, the effects of human capital not correlated with these variables will show up as TFP.

to use mainframe computers to handle payroll, and they developed new products and services. Thus, while the rise in TFP is not really a mystery, the exact source of the growth is hard to pin down. Formal R&D played a role, but good ideas, new business models, larger scale of production, new designs, and better ways of organizing production also contributed.[18]

Figure 7: Labor Productivity Growth (1948-2024)



Beginning in the early 1970s, the economy shifted markedly to a low-productivity regime as the growth rate of labor productivity fell by over half to 1.55 percent a year (figure 7). TFP growth which fell to 0.52 percent a year, was the largest contributor to the decline. Had TFP growth kept growing at the same rate, the decline in labor productivity growth would have been small. There was not a precipitous drop in the contributions of physical or human capital. The contribution of capital intensity declined modestly to 0.79 percent a year while the contribution of labor composition increased but remained small. Interestingly, with much lower growth in TFP, investment opportunities were likely to diminish, but measured accumulation of physical and human capital did not contribute to the drop in labor productivity.

[18] The problem for empirical economists is that we do not know how to measure and capture the diverse changes that took place. In practice, because TFP is measured as a residual—the amount of output growth that cannot be explained by input growth—it is sometimes called a measure of our ignorance.

No consensus has emerged among economists on the sources of the slowdown in TFP growth. Berndt and Wood (1975) and Baily (1981) argue oil price increases damped growth in the 1970s. Rising regulation, discussed above, may also have been a drag on productivity growth.[19] Public and private R&D investment slowed in the 1970s, a channel emphasized by Griliches (1994). Denison (1979) suggests union activism may have damped labor efficiency as well. David Aschauer (1989) proposed infrastructure as a cause of productivity growth in the 60s and then its subsequent slowing and Fernald (1999) zeros in on the waning effect of the Interstate Highway System in particular. More generally, Gordon (2016) argues that many of the innovations introduced from 1870-1970 were one-time improvements—public health improvements from sewer systems, for example. Consequently one should not expect ongoing productivity growth to follow once they have been completely adopted.[20]

The Growth Acceleration 1995-2004. Starting in the mid-1990s, there was a return to rapid productivity growth for about nine years. TFP growth more than tripled to 1.65 percent a year and capital deepening contributed 1.32 percent a year, an increase of ½ percentage point.[21] Labor composition added 0.26 percent a year, giving overall labor productivity growth of 3.26 percent a year, about the same rate as the period 1948-73. In terms of this decomposition of growth, the two periods are very similar, with a little less contribution from TFP in this latter period and a bit more from capital intensity.

The uncertainty in explaining productivity trends prior to the 1990s suggests the renewal of rapid growth might be a mystery too, but economists share a (rare) agreement over this period. The primary cause appears to have been a surge in the rate of improvement in information and communications technology. Table 1 shows the importance of computer and electronic products to productivity growth in the period of acceleration and their sharp slowdown after 2004. TFP in computers and electronic productivity increased to over 10% per year 1995-2004 and then dropped to 2.2% per year after that. Falling computer prices, the effect of TFP growth in

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[19] An alternative perspective on the environmental and workplace safety regulations that were put in place in the 1970s is that they diverted economic activity toward outcomes not recorded in GDP, such as environmental capital investment.
[20] Mokyr (2002, 2018) counters that the improvements in scientific practice and tools (inventions in methods of invention) that underpin many of those advances will continue to generate other advances.
[21] Some researchers have identified mismeasurement that damps the magnitude of the productivity boom, but the story is qualitatively the same (Byrne et al. 2013).

computer production and competition, led to a surge in investment in information technology in the late 1990s that increased aggregate output and productivity.[22]

Importantly, though, the boom did not come from a single cause. Other, sometimes complementary factors also contributed to the productivity acceleration. Gordon (2002) argues that cyclical factors were in play. As articulated in Basu et al. (2006), increases in utilization appear as TFP growth. However, utilization-adjusted TFP, reported by the San Francisco Federal Reserve using their methodology (Fernald 2014), tells quite a similar story for the acceleration, on balance. Bresnahan et al. (1996) and Bresnahan et al. (2002) emphasize that “co-invention” of business processes is necessary to exploit advances in IT. Oliner and Sichel (2000) note that restructuring of supply chains in retail and wholesale trade contributed as much to the early years of the boom as IT production did. Bernard et al. (2006) argue that responses to import competition from low-wage countries raised productivity for some firms. Jorgenson et al. (2008) note that fiscal consolidation, deregulation (in telecommunications, finance, and transportation), greater macroeconomic stability (“the Great Moderation”), and the payoff from greater confidence in monetary policy contributed as well.

Why did TFP growth in the computer and electronic products industry increase so much? A combination of market structure and technological change helps to explain the pickup. Computer performance had been improving rapidly since the 1950s, the transition to more reliable solid-state systems began in the 1960s, and “Moore’s Law,” describing seemingly inexorable progress in miniaturization, had been in force for 30 years before 1995. But, in the 1990s the chipmaker AMD started selling processors that were comparable to those from Intel, which now had real competition. This encouraged Intel to speed up the introduction of new generations of faster chips and this, in turn, meant that the quality of the personal computers improved rapidly.[23] Prices for memory chips, a fiercely competitive industry based largely in Asia, were also falling quickly.[24] Downstream from chips, competition in the computer industry

[22] The table is taken from presentations made by Baily to the Japan Productivity Center in February 2024 and to the productivity division of the Organisation for Economic Cooperation and Development.
[23] Whether this entailed more rapid innovation by Intel or an acceleration of the release of a backlog of designs is unclear. See the discussion in Goettler and Gordon (2011).
[24] Processors (MPUs) and memory chips used the same manufacturing process, with both fitting more transistors on a chip. MPUs incorporated the patented design of the chip and were sold at much higher prices than the memory chips.

had increased as well, driving product innovation up and prices down. When IBM entered the PC market, they made use of chips from Intel and software from Microsoft, so that other companies could use the same chips and operating system. The early models were not very user friendly, but the effective standardization created by IBM compatibility meant the market for applications software developed quickly, with word processing and spreadsheet programs making PCs useful to a much wider range of users.

The bulk of the step up in capital deepening in this period is related to ICT as well. In the 1980s, Robert Solow famously said that computers were everywhere except in the productivity statistics, a pithy but inaccurate remark (Solow 1987). Computers, in fact, were not everywhere. As noted by Oliner and Sichel (1994), computers were a very small share of the capital stock and therefore could not have had much impact on productivity at the time, though falling prices and an ICT ecosystem including software and networking drove the ICT share of capital stock up in the following years. During the 1990s, falling prices, a result of faster TFP growth and competition, fueled computer investment, creating a market for innovative software, which in turn drove computer investment in a virtuous cycle. In addition, the buildout of the Internet entailed massive investments. Originally created (as ARPANET) with the goal of fostering secure communication among research scientists in the early 1970s, with the creation of Transmission Control Protocol/Internet Protocol (TCP/IP) a much broader-based network became possible. In the 1990s, browsers, rapid modems, and more powerful PCs made practical widespread internet use possible and with the introduction of browsers to access crowd-sourced sites (the World Wide Web), internet use exploded. Meanwhile, communications equipment was improving by leaps and bounds as well (Doms 2005). Network usage proved hard to forecast and much of the network went unused in the early 2000s, causing a market correction and economic downturn, but usage eventually caught up with capacity.

Table 1 Industry Total Factor Productivity Growth (CAGR, % per year)

Industry	1987–1995	1995–2004	2004–2023
Private Nonfarm Business	0.48	1.52	0.64
Manufacturing	0.83	2.05	-0.02

Nondurable Manufacturing	0.22	0.63	-0.36
Durable Manufacturing	1.23	2.88	0.38
Computer and Electronic Products	7.41	10.27	2.24
Utilities	2.43	0.13	0.36
Construction	-0.29	-0.56	-0.80
Trade	1.56	2.55	0.17
Information	-0.09	0.89	1.53
Finance, Insurance, Real Estate, and Leasing	-0.43	-0.22	0.18
Services	-0.74	0.33	0.57

Source: U.S. Bureau of Labor Statistics, Total Factor Productivity tables (Major Industries and Major Sectors), release March 21, 2025. ChatGPT5 assisted in the updating of this table.

The general-purpose nature of computing and networking made it possible for industries across the economy to reorganize to exploit IT and raise productivity. It was natural that wholesale and retail trade were industries that could take advantage of the developing technologies. Large retailers such as Wal-Mart, Best Buy, Costco and Kroger saw the opportunity to spread around the country and drive out smaller or weaker and less productive competitors. This was aided by the strong economy of this period, with incomes and employment rising. The growth of online and internet sales also helped widen the use of computers.[25]

Slowdown Again, 2004-Present. In the mid-2000s, productivity growth and its components reverted to their 1973-1995 behavior—slower TFP growth and capital deepening. The primary source of the reversion to slow TFP growth is a broad-based drop in the manufacturing sector (figure 8).[26] In the 1987-2004 period, manufacturing contributed roughly half of all TFP growth in the economy.[27] Since then, on average, manufacturing contributes nothing. The primary cause of this drop is the computer and electronic products industry. High-volume production of

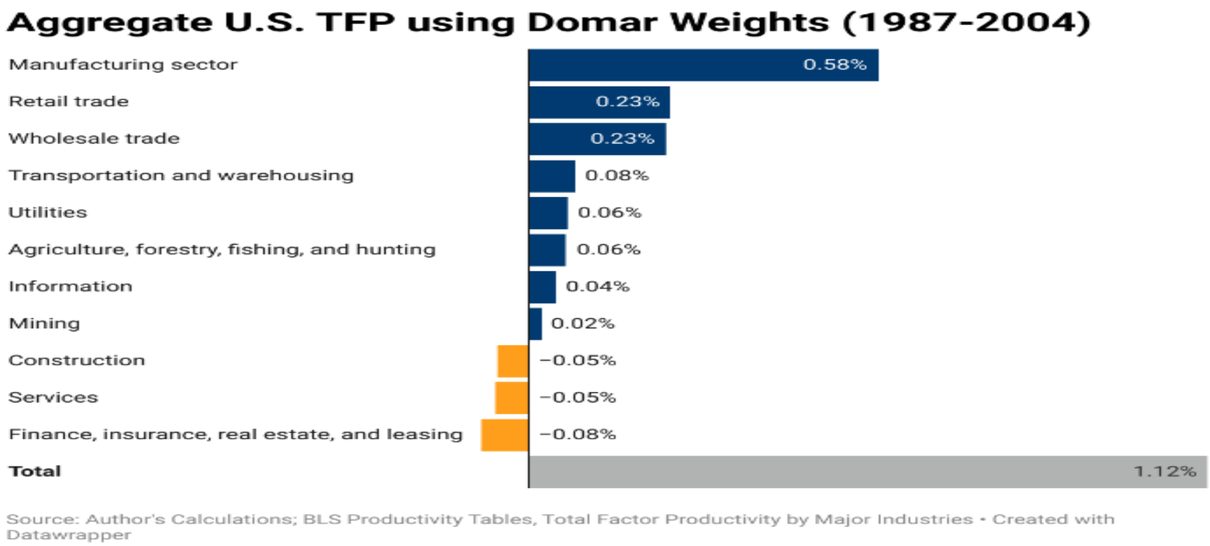
[25] Measurement changes also played a role. For many years, the government statisticians said they could not capture quality improvements in computers and electronics, but in the 1990s they developed techniques to do this, using hedonic regressions and matched model comparisons. This measurement change did not of course change reality, but it changed our perception of how fast productivity grew. However, the timing and size of these measurement problems does not appear to explain the productivity slowdown in the 2000s (Byrne, et al. 2016).
[26] Domar weights are used to account for intra-industry linkages. On Domar weighting, see Organisation for Economic Cooperation and Development, Measuring Productivity—OECD Manual, https://www.oecd.org/en/publications/2001/07/measuring-productivity-oecd-manual_g1gh2484.html
[27] We have also made the calculations of the contributions of each industry within manufacturing.

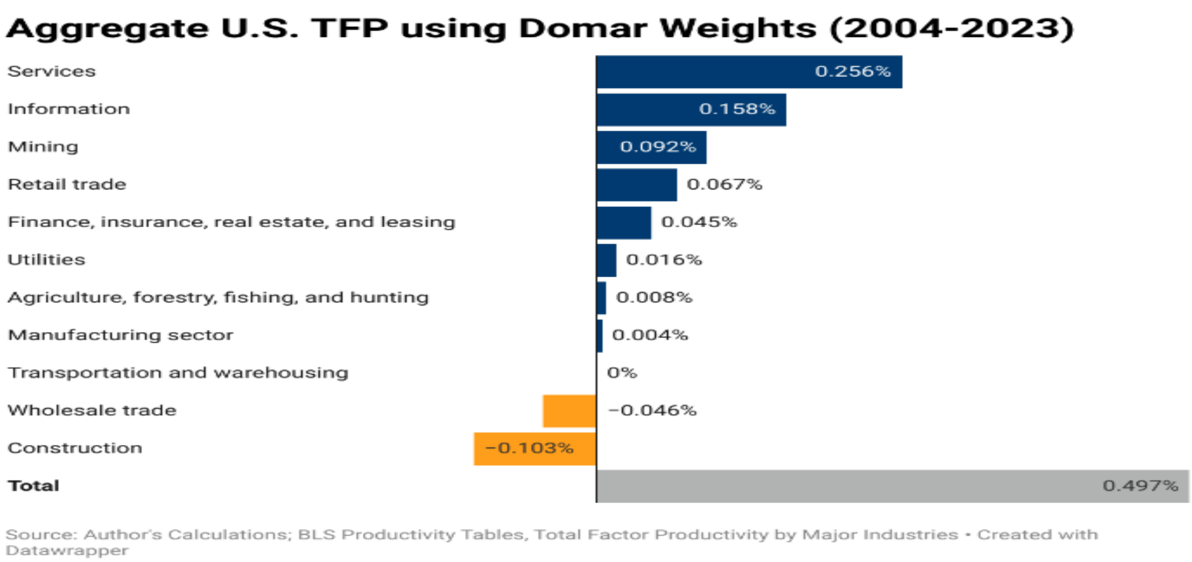
computers, cell phones, and peripheral devices has moved offshore since the accession of China to the World Trade Organization in 2001. Production of low-volume electronics for specialized defense, aerospace, and medical markets has remained in the United States (Byrne 2015). Design work for many IT products (as well as software development) has largely remained in the United States as well but is outside the manufacturing sector. These activities, which may appear in the information sector where productivity growth has risen, are an example of intangible capital investment, which has soared as a share of investment but is not fully captured in national statistics (Corrado et al. 2022).

Changes have happened in other sectors as well. Retail and wholesale trade were the next largest contributors during the boom, but their contribution has fallen to nearly zero. In the latter period, while services and information contribute the most, mining, retail trade and finance also show high contributions. Finance is quite important because it was a negative factor in the earlier period and shifts to a positive one, despite the financial crisis in 2008-09. The construction industry has been a perennial productivity laggard, but the quality of the data is not very good. Figure 8 shows that the locus of productivity growth in the business sector of the US economy has shifted towards services, with the top five contributors being service sectors. TFP growth in the total business sector was much faster in the early period, when manufacturing was driving the results, than in the latter period.

Figure 8: Sector Contributions to Aggregate TFP Growth[28]

[28] Note that the scales in the upper and lower panel are different





Conclusions and Implications for Policy Today. The period after the end of World War II was one of strong growth in the United States and many of the more advanced economies but for rather different reasons. In some, there was recovery after the destruction of the war, while in the United States there was the opportunity to use ideas and technologies that had been developed in the war or pre-war period. And the strong overall economic growth fostered new investment, new ideas and technological research. The period of rapid growth ended rather abruptly in the United States in the early 1970s for reasons that remain puzzling. The boom in the 1995-2004 period can safely be attributed in large part to ICT manufacturing and ICT investment. The reversal around 2004 can be attributed to manufacturing productivity growth falling to zero.

We have emphasized one conclusion from this section, which is that manufacturing is no longer driving productivity growth in the United States (see Table 1 or Figure 8). Productivity growth in high-tech has continued despite the limitations of Moore's law, with chip design still remaining as a very strong sector in the US. Since chips production itself, especially for the most advanced chips, are now largely made overseas, they provide a far smaller boost to manufacturing productivity.[29] Outside of high-tech, manufacturing companies have automated their operations or else moved production overseas to lower cost locations. These sources of productivity growth may have been exhausted, barring the introduction of a new wave of technology.[30]

One possible implication of this period is that policymakers should aim to keep the production of high-tech products within their own country. Both the U.S. and EU governments have gone down that road. Is it a good idea? In terms of national defense, it is surely unwise to have so much of high-end chip production located a few miles off the Chinese coast. In terms of boosting *measured* productivity growth, it would also be helpful to locate chip production at home. However, in terms of the kind of productivity that generates broad economic growth, the case for onshoring is much weaker. High-tech manufacturing facilities are very expensive to build and employ few people. The manufacture of chips was only a modest driver of the rise in incomes and wages in the United States in the late 1990s. Rather, what counted was the ability of companies to apply the new technologies and develop new and more productive business systems throughout the economy. Access to advanced chips and productive use of the enabled technology are more important for productivity than the location of their production. With changing global tensions, access to advanced chips could now become a greater issue affecting countries' resilience against shocks. Moreover, the most successful chip design companies, such as Nvidia, locate the bulk of their activity in the United States.

What policies contributed to the surge in productivity? Relatively generous direct support from government for innovation have been important to technology development in the United States. Government support, especially from the Defense Department, has been crucial for digital technology development (Flamm 1988). Another possible reason for the productivity surge is

[29] A substantial share of the *design* of chips takes place in the United States, a highly innovative activity not included in manufacturing in government statistics (Bayard et al. 2015).
[30] See Appendix B for the latest projection on the impact AI on growth and productivity. Baily et al. (2025).

the program of deregulation in the 1980s. Baily and Solow (2001) review studies of international comparisons of productivity and find that regulations that limit competition and restrict trade tend to reduce a country's relative productivity. There is some evidence that more regulation negatively impacts productivity growth. Davies (2014) shows that, from 1997-2010, industries with the least binding regulations experienced 90% higher growth in output per person and 88% greater growth in output per hour than industries with the most binding regulations.

In addition, Nicoletti and Scarpetta (2003) find that privatization and entry liberalization are associated with positive impacts on productivity growth across industries. The paper looks at two groups of industries: manufacturing and non-manufacturing/services. It finds that privatization alone is not enough for non-manufacturing industries and must be paired with effective access regulations and market liberalization in competitive segments. In addition, the paper shows evidence that high-tech sectors benefit most from low entry barriers and competitive pressure, and for sectors that rely on ICT and R&D, the negative impact of regulation is amplified.

The impact of regulation on productivity depends on the nature of regulation. In the financial sector, we know that light-touch regulation failed to control excessive risk-taking in the early 2000s, leading to the financial crisis. Better regulation and enforcement in the markets for mortgages and asset-backed securities may have prevented this crisis.

Instead of hurting growth, environmental policies can support productivity growth, eliminating the tradeoff between regulation and productivity in this area. Regulations of the environment have been researched extensively within literature. An underlying theory of this literature is the Porter hypothesis, which posits that environmental regulations can lead to the discovery and introduction of cleaner technologies and environmental improvement (Porter 1991; Porter and van der Linde 1995). There are two versions of this hypothesis: the strong and narrow hypotheses. The strong version posits that the advantages gained from increased innovation driven by environmental regulations ultimately outweigh the associated costs, leading to a rise in overall productivity. Meanwhile, the narrow hypothesis states that market-based tools such as taxes or tradable permits can be more effective at promoting innovation and boosting productivity. This is because they grant firms greater flexibility in selecting the most efficient technological solutions to reduce compliance costs, unlike non-market-based instruments (De Santis et al. 2020).

Many studies testing this hypothesis find that environmental policies promote productivity growth, patent development, and R&D investment (De Santis et al. 2020; Jaffe and Palmer 1997; Kneller and Manderson 2012), while others find little to no evidence (Rexhäuser and Rammer 2014; Rubashkina et al. 2015).[31]

Overall, it is hard to say whether policies had a major influence on the productivity surge 1995-2004, or which policies had the largest impact. There was a technology cycle that bore fruit during this period. Although the evidence is not definitive, it seems likely that the policy environment in the United States was helpful in making it easy for companies to buy land and to adjust employment to take advantage of the new technologies and business models. For example, wholesale and retail trade made big contributions to the productivity surge which was possible because big box and specialty retailers were able to expand and drive out less productive retailers. More restrictive zoning laws or labor regulations could have slowed this process down.

Recent research has surfaced the importance of reallocation to the pace of TFP growth (Decker et al. 2020; Mischke 2025). TFP comes from innovations at incumbent firms and the creation of innovative startups, but the rate at which capital and labor are reallocated to those more productive uses plays an important role and contributed to the period of rapid growth after 1995.

The next section looks at the issue of regulation and progress in AI.

IV. Productivity Policy in the AI Era

AI regulation has been a focal point of policy debates in recent years, as policymakers and researchers are concerned about the impacts on the labor market and the future of work, on individual and corporate privacy, and on intellectual property rights. While some regulation may be necessary to manage societal risks, an overly restrictive regime could delay or dilute the significant productivity gains AI might unlock. We begin with a review of recently implemented policies in the United States and Europe, and then provide a critical review and consider the Trump Administration's new AI policy framework.

IV.1 Alternative Regulatory Frameworks for AI

[31] For a detailed summary of empirical studies testing the Porter Hypothesis, see Table 1 of Martínez-Zarzoso et al. (2019).

Regulatory regimes are only just being built to support AI usage and development. Themes include transparency when AI is used—such as in the creation of images, especially "deep fakes", protections against discrimination, guaranteeing the right to an explanation of AI decisions such as in hiring—and an appeal process and levels of scrutiny that correspond to the perceived risks in AI use.

The European Union Framework

The EU AI Act, passed by the European Parliament and Council, which contains 113 articles and is spanning 144 pages, went into force in August, 2024.[32] The act provides a four-level framework to classify AI systems according to risk and describes the obligations of parties developing and deploying AI systems.

- Unacceptable risk: Certain types of activity are considered to pose unacceptable risk and are prohibited under the act, such as biometric categorization according to "sensitive attributes" such as race.
- High-risk systems: Systems used in law enforcement, for example, are required to establish a risk-management system, comply with data governance requirements, provide technical documentation, keep records, provide instructions for proper use, implement human oversight, establish a quality management system, and meet standards for accuracy, robustness and cybersecurity.
- Limited-risk systems: Systems interacting directly with humans are required to be transparent, meaning they must inform the user they are interacting with an AI system, mark AI-generated audio, video, image, and text output as such, and so forth.
- Minimal risk systems: All other systems, such as AI-enabled video games and spam filters, are unregulated.

U.S. Law at the State Level

[32] See "High-level summary of the AI Act," https://artificialintelligenceact.eu/high-level-summary/.

All 50 U.S. states have passed or are actively debating legislation on AI as of 2025.[33] More than 1,000 bills have been introduced in state legislatures since 2024 and 141 have been enacted. Among the most active states are California, which has passed 10 laws, Colorado, which has a comprehensive framework, and Texas, which provides an "AI sandbox" for safe exploratory use of new systems.[34] This has led to a complicated landscape for AI companies to navigate and AI companies have lobbied for a single federal regulatory framework.[35] Legislation has been introduced but not passed by the U.S. Congress proposing a moratorium on state regulations justified by jurisdiction over interstate commerce.[36] Both the Biden and Trump administrations have put a framework in place by executive order in lieu of legislation.

The U.S. Framework under President Biden

Through executive order, the Biden administration promulgated rules for executive branch agencies regarding the use of AI and imposed requirements on private parties producing and distributing AI systems (Executive Office of the President 2023).[37]

For the federal government, this order identifies broad principles and priorities for government offices, each described at length:[38] Government use of AI must be safe and secure; promote responsible innovation, competition, and collaboration; support American workers; advance equity and civil rights; protect privacy and civil liberties, and so forth. And, "the Federal Government should lead the way to global societal, economic, and technological progress, as the United States has in previous eras of disruptive innovation and change." In 2024, the Office of

[33] See "Artificial Intelligence 2025 Legislation" at the National Council of State Legislature's website, http://
[34] See "Blue, Red, Purple State: What California, Texas, and Colorado Teach Enterprises About AI Regulation," *The AI Journal*, July 9, 2025.
[35] See the proposal submitted by OpenAI to the White House Office of Science and Technology Policy, March 13, 2025. https://cdn.openai.com/global-affairs/ostp-rfi/ec680b75-d539-4653-b297-8bcf6e5f7686/openai-response-ostp-nsf-rfi-notice-request-for-information-on-the-development-of-an-artificial-intelligence-ai-action-plan.pdf
[36] See, for example, House Resolution 5388, the American Artificial Intelligence Leadership and Uniformity Act.
[37] The *Take it Down Act* makes it a crime to share non-consensual intimate "deepfake" images generated by AI.
[38] See "Advancing Governance, Innovation, and Risk Management for Agency Use of Artificial Intelligence ," https://www.whitehouse.gov/wp-content/uploads/2024/03/M-24-10-Advancing-Governance-Innovation-and-Risk-Management-for-Agency-Use-of-Artificial-Intelligence.pdf .

Management and Budget (OMB) provided concrete steps for agencies to take.[39] Examples of steps required by OMB are the following: (1) Agencies must designate a Chief AI Officer (CAIO) tasked with promoting the use of AI and reducing barriers to its use including in the areas of "IT infrastructure, data, cybersecurity, workforce, and the particular challenges of generative AI." (2) The memo also directs CAIOs to manage risks to safety and rights, recommends practices to manage AI risk in procurement, and establishes categories of AI that are "presumed to impact rights and safety." For those categories, agencies are required to assess potential risks and weight them against benefits in an "AI impact assessment" test the AI for performance as intended, monitor these determinations on an ongoing basis, and provide training and public documentation. (3) In addition, for rights-impacting AI, agencies must take further steps, such as mitigating algorithmic discrimination and soliciting public feedback. Further requirements for procurement include verifying that data used to train AI is lawfully collected and used, ensuring the AI developer is not relying on test data to train the system, check that the vendor is using environmentally efficient and sustainable development, and others.

Through procurement requirements, these directives for federal agencies will impact private business. In addition, these orders had several provisions that support smaller AI business, possibly improving productivity growth by enhancing innovation. For example, the Federal Trade Commission (FTC) has been directed to ensure fair competition in the AI marketplace using its rule-making authority and to provide computational resources to small businesses that would not otherwise have access to it. Biden's AI executive order also launched a pilot program to develop the National AI Research Resource (NAIRR), which is a shared platform that could provide AI researchers and students with expanded access to computational resources, educational tools, and high-quality data (National Artificial Intelligence Research Resource Task Force 2023). This resource could help promote innovation in the AI space, leading to new inventions that could raise productivity growth. Legislation has also been introduced to establish the NAIRR, which would codify the program into law and provide students, researchers, non-

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[39] The Office of Management and Budget memorandum, "Advancing Governance, Innovation, and Risk Management for Agency Use of Artificial Intelligence," notes that AI management is "deeply interconnected with other technical and policy areas including data, information technology (IT), security, privacy, civil rights and civil liberties, customer experience, and workforce management." Broader statutes in those areas apply to AI as well.

profits, small businesses, and academic institutions access to the resources needed to develop AI systems (Obernolte 2023).

This executive order, however, did implement reporting requirements that force companies developing the most advanced AI models to disclose information on training, model weights, and safety testing to compete for federal government contracts. This rules could slow innovation by bogging down the development process of development and discouraging companies to run thorough safety tests, since results need to be shared with the government. Further, smaller firms in particular are less equipped to comply, making it more difficult for them to get ahead of the major players, which would harm AI-driven productivity growth. Moreover, the compliance burden on the executive agencies is substantial as well.

The Trump Administration Framework

In July, 2025, the second Trump administration published "Winning the Race: America's AI Action Plan". Compared to the Biden administration, Trump's has taken a starkly different approach to AI regulation, emphasizing a market-driven and hands-off regulatory approach. This regulatory approach is outlined in the Trump administration's major AI policy document, the AI Action Plan (The White House 2025). This plan included three pillars of policy recommendations: Accelerate AI Innovation, Build American Infrastructure, and Lead in International AI Diplomacy and Security.

The first pillar outlines several regulatory changes to AI policy, including removing regulations that burden AI development and deployment and hinder innovation. It also highlights the need for workforce development and retraining, emphasizing AI-labor complementarity. Specifically, the action plan aims to remove red tape and onerous regulation by, for example, directing the Office of Science and Technology Policy (OSTP) to release a request for information from industry about what regulations are hindering AI innovation and adoption. This will likely help tech companies innovate and develop new models without the burden of AI regulations, which could help fuel productivity growth.

The first pillar also includes directives to enable AI adoption and encourage open-source and open-weight AI. Open-source and open-weight AI could help fuel adoption, leading to productivity growth by giving firms low-cost, easily accessible tools they can integrate into their business processes and improve firm performance. As more firms adopt AI and incorporate them into their business models, they will likely see gains in output and productivity from its adoption.

Research and development are key to unlocking productivity growth, and the AI action plan includes several key provisions to advance the science of AI and AI-enabled science. This includes investing in cloud-enabled labs for a range of scientific fields and prioritizing investment in research that preserve America's leadership in finding new paradigms that advance the capabilities of AI.

While the Trump administration has focused on a hands-off regulatory approach, if the AI regulations function like environmental regulations, the sector could miss out on key productivity growth and innovation, contrary to what according to the Porter Hypothesis suggests. Furthermore, a lack of regulations has its own risks, as AI poses several national security risks and can promote harm (Toh 2025). This perspective suggests that regulation, when designed effectively, can serve not only as a constraint but also as a catalyst for technological progress by pushing firms to innovate in ways that comply with higher standards. In the absence of such guardrails, the AI sector may experience rapid short-term growth, but this growth could be fragile and potentially be undermined by issues such as biased algorithms, lack of accountability, and unsafe deployment practices. Moreover, without a coherent regulatory framework, firms may underinvest in trustworthy AI systems, leaving the U.S. vulnerable to ethical, economic, and security challenges. In contrast, strategic regulation could set clearer expectations for safe development, protect consumers, and build international trust in U.S. AI leadership, thereby sustaining long-term innovation and productivity growth.

Assessing pathways towards effective AI regulatory policies Ultimately, fostering innovation and productivity in AI will likely require a more nuanced approach: one that avoids stifling development with excessive regulation, ensures open access to infrastructure and data, and maintains competitive pressure on incumbents. A pro-competition strategy—through support for startups, vigilant antitrust enforcement, and targeted, use-based regulation—could offer the best path forward.

While effective regulation can serve important roles in correcting market failures and protecting public interests, policymakers should carefully consider both compliance burdens and how firms respond strategically to regulatory constraints. It is estimated that 3% of total working hours in the U.S. is devoted to compliance activities in an average year (Kalmenovitz 2023). As a result, regulations can create incentives that encourage strategic behavior to arbitrage regulation.[40] To develop efficient AI regulations, it will be important for policymakers to design rules that balance necessary protections while facilitating economic growth and dynamism.

The stakes of correctly managing AI technology with regulation are high. Innovation in this field often requires massive computational resources and data access, giving large firms a natural advantage. Competition is essential for innovation and productivity. Without competitive pressure, incumbent firms have fewer incentives to innovate or share the benefits of AI more broadly.[41] This raises fundamental policy questions: Should regulators focus on reining in big tech firms to preserve space for smaller players? Should policy support emerging AI startups directly? Or should market forces determine winners and losers?

A further market-failure dimension concerns the environmental externalities of AI's infrastructure. The rapid build-out of data centers required to power large AI models imposes significant carbon emissions, water use, and strain on grid capacity. Yet, the cost of energy supplied to these facilities doesn't reflect their upstream climate and health damages, absent a carbon price. For example, U.S. data centers are estimated to consume over 4% of national electricity and emit more than 105 million tons of CO_2e, with over half of that power coming from fossil fuels (Guidi et al. 2024). The amount of CO_2e emitted per unit of electricity consumed also exceed the U.S. average by 48%. Because much of AI usage is priced at zero or on a flat subscription (rather than on a marginal per-use) basis, users have little incentive to economize on queries, leading to overuse beyond what would be socially optimal. This "free ride" model mirrors classic Silicon Valley growth tactics which, if unchecked, may create a kind

[40] For example, financial institutions might shift assets to meet mandated requirements while quickly reverting back to riskier practices after supervisory reviews (Abbassi et al. 2025). Size-contingent regulations can also distort market outcomes, as firms may deliberately limit growth to avoid crossing thresholds that trigger additional compliance costs (Garicano et al. 2016). Such boundary-driven reallocations appear in tax policy as well with corporations strategically shifting operations to minimize tax exposure (Hines and Rice 1994; Giroud and Rauh 2019).

[41] For a more complete analysis see Aghion et al. (2005). There is also a valuable analysis of policy and innovation in Aghion et al. (2021).

of digital tragedy of the commons in which the public bears the environmental damages and costs while usage keeps exploding.

IV.II Immigration Policy

High-skill immigration plays a key role in the tech sector and innovation. The tech sector is a large driver of economic growth and immigrants, particularly high-skilled immigrants, play a large role in creating economic growth in the tech sector.

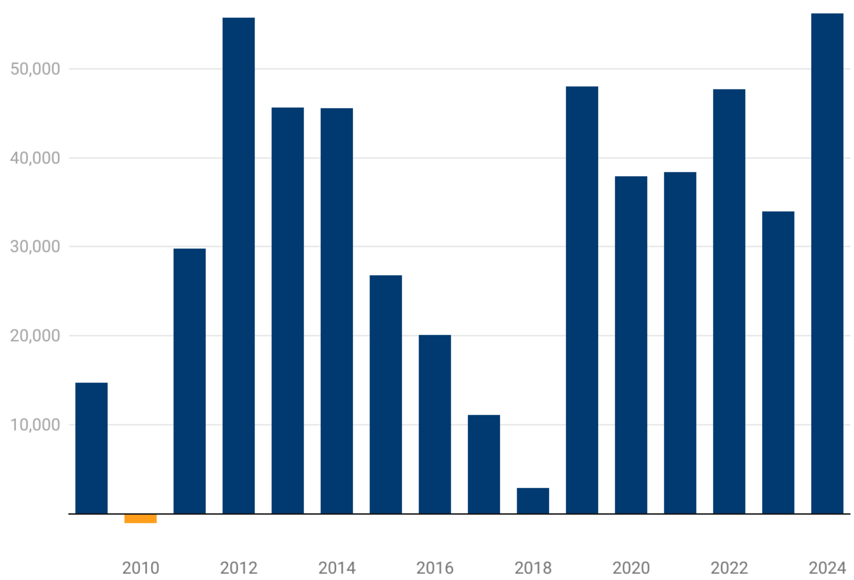
Temporary high-skill immigration in the U.S. is often in the form of H-1B visas, the largest program for temporary skilled migration in the U.S. These are visas that allow companies to “employ foreign workers in occupations that require the theoretical and practical application of a body of highly specialized knowledge and a bachelor’s degree or higher in the specific specialty or its equivalent.” Other means of high-skill immigration include work or student visas, green cards, or other talent visas such as the O-1 visa.

The H-1B visa program allows firms to apply to the U.S. government to sponsor a skilled foreign worker for three years, where the worker must remain at the sponsoring firm for the entire duration (unless the worker obtains another visa or permanent residence). Following the three years, there are a few possibilities: the worker leaves the U.S., the firm can seek to renew the H-1B, the firm can sponsor the worker to be a permanent resident, or the worker could exit the firm but stay in the U.S. through other means (such as another visa or obtaining permanent residence).

Congress has set a limit on the number of H-1B visas available each year since the program's creation in 1990. Currently, there is a cap on the total number of new H-1B visas issued at 65,000, plus an additional 20,000 for workers with a master’s degree or higher from a U.S. higher education institution (American Immigration Council 2025). This cap has led to a shortage in the number of H-1B visas, as the number of applications outweighs the number of available visas. In 2024 alone, approximately 400,000 H-1B applications were approved, 35% of which were new applications. This means that there was a shortage of about 55,000 H-1B visas in 2024 (See Figure 9).

Figure 9: HI-B Visas 2009-24.

Shortage of H-1B Visas, Fiscal Years 2009-2024



Source: USCIS, H-1B Employer Data Hub, Author's Calculations • Created with Datawrapper

High-skilled immigration from the H-1B program is highly concentrated in the tech sector. Some of the largest tech companies such as Google, Meta, and Microsoft are included in the top 15 most accepted beneficiaries of H-1B visas. In addition, almost two-thirds of all approved H-1B beneficiaries were in computer-related occupations in 2023, while no other occupational group surpassed 10% of all approved H-1Bs.

Figure 10: H-IB Visas by Type of Employer

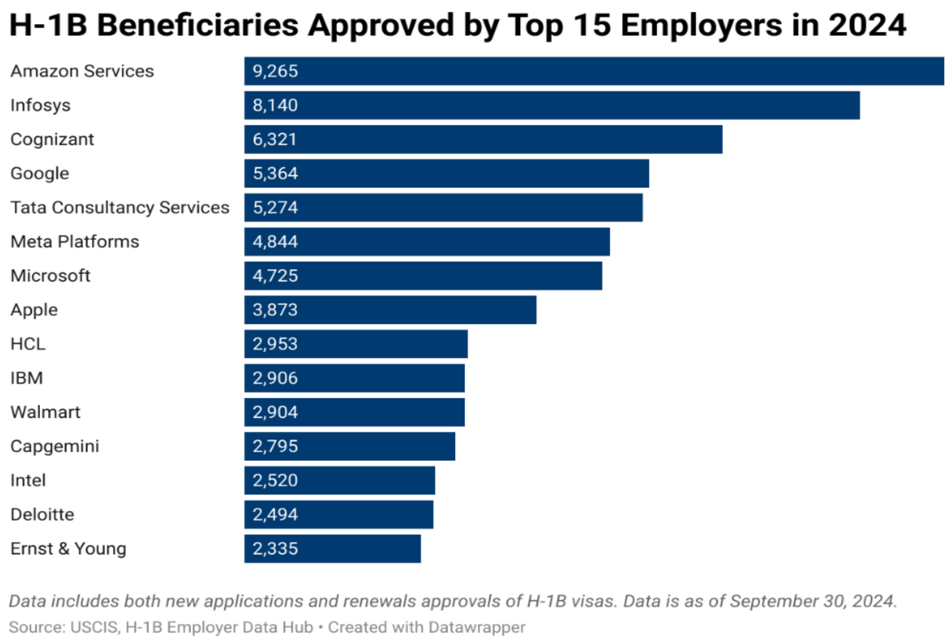
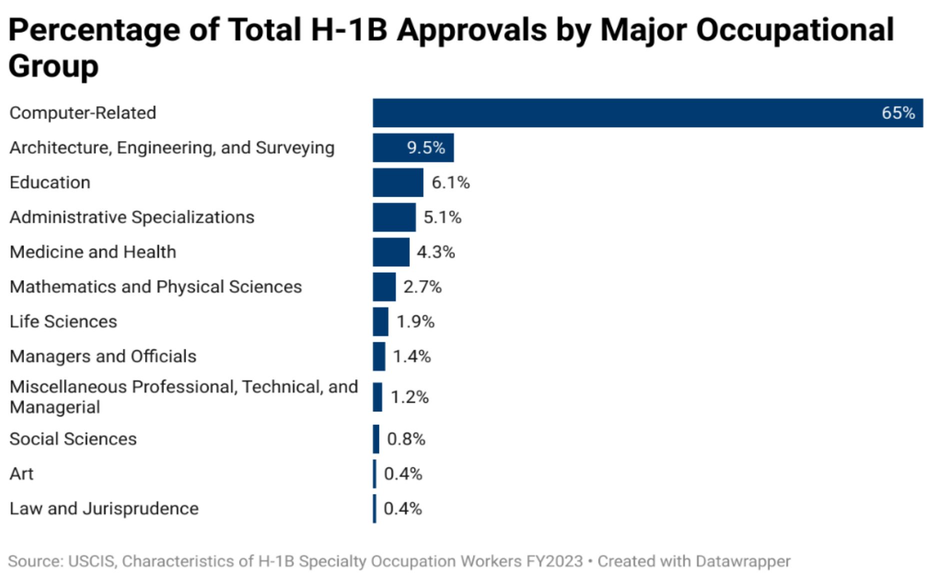


Figure 11: H-IB Visas Approved by Occupational Group



The literature on the effects of H-1Bs and high-skilled immigration on innovation shows suggestive evidence that highly skilled immigrants play a key role in innovation. Bernstein et al. (2022) utilize data on Social Security Numbers (SSN) to identify immigrant inventors in patent data, finding that 23% of patents between 1990 and 2016 were produced by immigrant inventors. In addition, Hunt and Gauthier-Loiselle (2010) and Hunt (2011) utilize the 2003 National Survey of College Graduates to show that high-skilled immigration led to more+ patents and innovation.

Specifically, immigrants with a 4-year college degree were twice as likely to have a patent than US-born college graduates (Hunt and Gauthier-Loiselle 2010).

There is suggestive evidence that high-skilled immigration improves the U.S. economy: immigrants contribute to entrepreneurship and business dynamism and have positive fiscal effects. Immigrants account for 25% of all new businesses each year and have founded 55% of all "unicorn" startups—startups valued at $1 billion or more. This helps improve job prospects and wage growth as startups contribute 20% of new jobs created in a year. Further, one analysis suggests that 32% of total U.S. innovative output since 1990 can be attributed to U.S.-based immigrants (Bernstein et al. 2022). In addition, high-skilled immigration improves the federal budget by adding approximately $39,500 per worker, contributing even more to subsequent years as wages rise. Per household, this number rises to $40,000 (Ozimek et al. 2025).

To raise productivity and economic growth, the H-1B visa program could be reformed to better accommodate more highly skilled workers. For example, to end the shortage of H-1B visas, the cap of H-1B visas could be eliminated or extended. However, other policy analysis argues that the H-1B program does not effectively prioritize workers who will contribute the most to economic growth. For example, a 25-year-old applicant will earn more in the long run than a 40-year-old with a similar offer. The H-1B program could be reformed to prioritize younger, higher-salaried offers to improve the fiscal benefits of the program. This could be seen as a reform to the current program or a complete change to a "skilled worker visa" program(Ozimek et al. 2025).

Recent reforms have done the opposite and attempted to restrict the H-1B program. On September 19, 2025, the Trump administration released an executive proclamation to impose a $100,000 fee on companies requesting new H-1B issuances (The White House 2025). This policy could have negative effects on the economy and innovation by leading to brain drain and constrained competition. For example, because of this change smaller tech companies will face greater hurdles to getting skilled foreign labor, solidifying large companies' market share in the market and constricting innovation. Further, this change could lead to brain drain, as foreign students will be more likely to leave the country after graduation (Almeida 2025).

V. Policies for the Coming Labor Market Disruption

The integration of AI into various sectors of the economy is poised to significantly reshape the labor market. Where previous bouts of automation mainly affected low- and middle-class jobs, AI has the potential to automate white-collar, cognitive tasks. If AI leads to more automation, this could result in large declines in labor demand, depressed wages, and diminished job opportunities.

A significant percentage of the labor market is exposed to AI automation. Estimates suggest that between 19% and 30% of workers may see at least 50% of their job tasks automated (Eloundou et al. 2024; Kinder et al. 2024). While task exposure doesn't automatically imply a job will be automated, it does mean that there is greater risk of automation for that occupation. Notably, only a small share of tasks, less than 10%, are both core to a job and currently performable more effectively by AI (Goldstein 2025).

Certain sectors are more susceptible to AI-induced disruptions. As mentioned earlier, AI exposure is concentrated in a set of cognitive tasks, especially in middle- to higher-paid positions. In contrast to previous periods of technological change that have been skill-biased, meaning they mostly substituted for routine skills in middle and some low-income positions, AI could automate many high-skilled tasks such as computer programming, tax preparation, and insurance underwriting (Kinder et al. 2024).

AI exposure has also been linked to changes in wage growth. For each occupation, every one unit increase in AI exposure is associated with a 0.74 percentage point decrease in annualized wage growth (Goldstein 2025). AI automation negatively impacts wages in low-skilled occupations while AI augmentation fosters higher wages for high-skilled occupations (Marguerit 2025). This pattern may change in the future with the onset of generative AI, which has greater applicability in high-paying, cognitive jobs. The ultimate impact will depend on the degree to which generative AI augments or automates jobs.

While employment has grown robustly after the introduction of AI in late 2022, employment growth for younger workers has stalled, particularly those most exposed to AI (Brynjolfsson, Li, and Raymond 2025). This pattern suggests AI may be driving seniority-biased technological change, disproportionately benefiting experienced workers at the expense of junior employment (Lichtinger and Hosseini 2025).

Furthermore, the search and matching dynamics of the labor market could be severely altered by AI. For employers, AI technologies have reduced private search costs, as is evident from the increase in job posting volume and the advent of software for screening candidate resumes and applications. For job seekers, these technologies reduce the marginal cost of submitting an application, leading to a larger applicant pool. However, such technologies are not always welfare improving, for example, as seen with the advent of internet job search (Kuhn and Skuterud 2004). For the modern era, early evidence suggests that AI has impeded labor market dynamics, as employers with lower hiring intent have increased job posting volume, while any discernible increases in matching efficiencies have been elusive (Wiles and Horton, 2025).

AI's impact is not uniform across all demographics. For example, the Latino population is overrepresented in fields at risk of automation (Figueroa 2025). In addition, women lag men's adoption of generative AI technologies: women's adoption of generative AI was roughly half that of men in 2023 (Hupfer et al. 2024), though recent evidence suggests the gender gap of adoption has closed over time (Chatterji et al. 2025). Disparities across demographics could further exacerbate existing inequalities in the labor market.

While labor market impacts of AI are in its early stages, it is important to highlight important mitigating factors. Adverse relative employment effects associated with AI have so far been concentrated in particular occupations, industries, or age groups (Abel et al. 2025; Crane and Soto forthcoming). Workers that are able to reallocate their time to non-AI-exposed tasks may avoid displacement, and in some cases, face higher demand for their labor (Hampole et al. 2025; Brynjolfsson, Korinek, and Agrawal 2025). Ultimately, aggregate employment effects hinge on whether AI complements or substitutes for AI-exposed workers. If AI acts primarily as a complement, shifting their demand curve outward, employment could rise, particularly when demand is highly elastic.

Although economy-wide impacts have been modest *so far* (Humlum and Vestergaard 2025), more significant changes could occur as the impact of AI on the labor market becomes more evident, underscoring the urgency of preparing workers for a more automated economy. The ambiguous effects of AI on productivity and employment call for nuanced policy responses that balance the promotion of innovation and the protection of workers' interests. This could include reskilling initiatives, which would help shift labor towards more productive uses in instances of automation. The U.S. spends less than 0.1% of its GDP towards reskilling and retraining programs; expanding training programs would help shift displaced workers into occupations not at-risk of automation (Baily and Kane 2024; Holzer 2023). Policymakers could promote portable healthcare options that eliminate job-lock frictions to enhance voluntary job mobility and talent reallocation in AI-intensive sectors (Madrian 1994). Similarly, policymakers should consider legal frameworks that protect core intellectual property through targeted non-disclosure agreements while limiting the impact of NDAs on impeding labor mobility (Fallick et al. 2006). Such pro-innovation policies would allow newer tech firms to flourish while limiting incumbents' unfair advantages in the AI market.

VI. What are the Most Important Policy Priorities, Based on the US Experience?

It is important to start this section with a caveat. In this paper we do not make specific policy recommendations, instead we will look at alternative policy options and discuss some of the pros and cons of these.

Taking Advantage of Artificial Intelligence

As we have already noted, there has been a tremendous push from the private sector, both to develop improved AI programs and to make these programs attractive to businesses wanting to improve efficiency and cut costs. The current Administration has loosened regulatory constraints on the technology sector which has the potential to increase the productivity impact of AI. To take advantage of the developments in technology, companies outside the tech sector will have to learn how to use the new technology effectively. [42]

There are dangers inherent in the new technology that we have described in this paper. Light touch regulation is great until things go wrong. AI programs can hallucinate and show bias. There are plenty of bad actors around, in the United States and around the world, that may be able to use AI for nefarious purposes. There is a case for having a regulatory body that can make sure AI does not become an instrument for criminal or just damaging behavior.

The most common fear is that AI will lead to unemployment. If the new technology does succeed in raising productivity it will displace workers from jobs. Displacement due to automation is not

[42] See Appendix B for the latest projection on the impact AI on growth and productivity. Baily et al. (2025)

a new phenomenon and in a flexible economy like that of the United States new jobs will be pcreated. A rise in productivity generates higher national income, which then leads to higher spending and raise the demand for labor. Evidence of widespread unemployment has yet to be reflected in aggregate statistics, though monitoring technological and economic indicators will be imperative to understand the transformative power of AI (Brynjolfsson, Chandar, and Chen 2025; Kinder et al. 2025).

More concerning is the fear that AI will contribute to the deskilling of jobs. This has been a real concern as the relative demand for labor has shifted towards college-educated workers and away from those with only high-school educations. It is not yet clear whether AI will continue that trend or will instead lead to a reduction in the demand for educated labor, in law or research, for example. If AI is combined with robotics, this could result in the elimination of many of the remaining blue-collar jobs in manufacturing, triggering losses of job opportunities and hardship in some communities. Past or future concerns about the loss of blue-collar jobs in manufacturing often ignore the existence of many blue-collar jobs in services, for which workers are often in very short supply. It seems likely that plumbers, auto mechanics, construction workers, and heating and air conditioning technicians, for example, will remain in demand.

The flexibility of the labor market in the United States will be an advantage in adjusting to the shifts in the labor market from AI. On the other hand, the weakness of the social safety net and the lack of good training programs are a disadvantage. While the US has a mixed track record of successful training programs, there is a network of community colleges that could provide new skills to the US workforce and help the adjustment process.

In summary: the main responsibility for taking advantage of AI lies with the private sector. The large technology companies are in a race among themselves and with China to develop the best technology. The easing of regulations will make model development easier. On the negative side, it does not seem the US government has put in place qualified policies to make sure large negative outcomes are restricted. Plus, if large tech companies engage in anti-competitive behavior it is unclear what type of support the government could provide to control such behavior. In addition, there is relatively little money being allocated to help workers adjust to the new technology and the changing structure of jobs.

Sustaining Competitive Pressure beyond the Tech Sector

Competitive pressure in an industry encourages companies to innovate and look for ways to cut costs and move ahead of their competitors. However, the relation between competitive pressure and innovation is complicated. Too little pressure means that companies can become complacent and implicitly (or explicitly) work together to avoid the costs and risks of innovation, but if there are too many companies and none of them are large enough or profitable enough to pay the cost of innovation, then again innovation may be slow. Judging when to bring antitrust actions in an industry is a tough decision and antitrust policies have not always been used well in the United States historically. Still, the threat of antitrust actions has provided a restraint on anticompetitive behavior. A vigorous independent Department of Justice is essential in sustaining the right amount of competitive pressure.

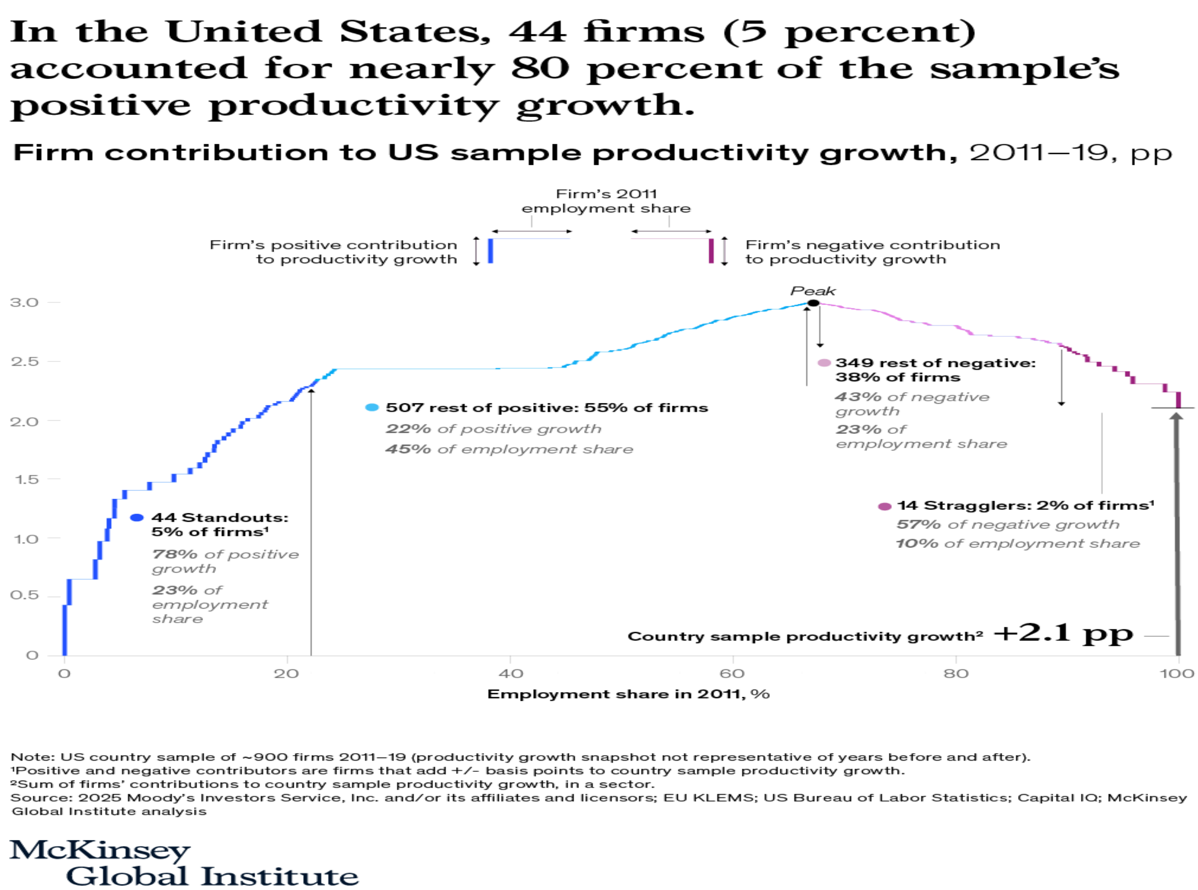
An important source of competitive pressure comes from international competition. Imposing large tariffs that reduce the volume of international trade can be expected to have a negative impact on productivity. This is especially true with the large and highly variable tariffs currently being imposed. Domestic industries lack the ability to fill the gap when imports disappear suddenly, while companies in foreign countries are being adversely impacted. The current US policy regime is a recipe for reducing productivity both here and overseas. After many years of increased globalization, established supply chains have developed, so that shifting these quickly or negotiating elaborate rules of origin can be economically unviable.

One qualification to this conclusion is that the US market is so large that when tariffs or trade restrictions are imposed, this may induce productive foreign companies to increase their production in the United States. This happened following President Reagan's imposition of quotas on Japanese autos. There are plans to increase domestic US manufacturing because of increased trade barriers, although such factories will be highly mechanized and will take time to be established. The auto industry is one example where domestic production is being ramped up (England 2025). In order to make major investments in facilities in the United States, companies will need stability and confidence that policies will not be suddenly changed.

Spreading Productivity More Widely

In Figure 8 it was revealed that the contributions to productivity growth were concentrated heavily in a few industries. Until recently the biggest contribution came from manufacturing, but further disaggregation indicates that computers and semiconductors were by far the most important source of growth over that period. Within wholesale and retail trade, the contributions to productivity growth came disproportionately from a small number of big box stores. A report published by the McKinsey Global Institute (MGI) in May 2025 found that 80 percent of the productivity growth 2011-19 among a sample of US companies was concentrated in just 5 percent of the companies (Mischke et al. 2025).[43] Figure 13 illustrates the findings for the United States. This analysis of individual companies reinforces the idea of the concentration of growth.

Figure 13: Breakdown of US Productivity Contributions by Firms



The MGI report also looked at Germany and the UK with rather similar results, except that the large companies in the UK did not perform as well in productivity terms as did the large companies in the United States and Germany. A major area of difference is that both Germany and the UK kept afloat a long tail of low-performing companies which dragged down overall

[43] Baily was a paid advisor to this project.

productivity performance. In the United States sample, there were also stragglers that lowered overall productivity growth, but much less than in the German and UK samples.

One implication of these latest findings goes back to a point made earlier. Strong competitive intensity in an industry will mean that the weakest, least productive companies will either be forced to improve their performance, or else fail. Also, as Decker et al. (2020) have shown, historically a lot of productivity growth has been achieved because the most productive companies expand and the least productive contract. They found that this mechanism has faltered in recent years, but in the MGI analysis, a lot of total productivity growth still came from reallocation, where productive firms increased their employment share and less productive firms lost share.

While the laissez faire regulatory environment in the United States should help wean out the less productive firms, the MGI study also found that there is an important contribution to productivity growth coming from firms that had fallen behind and then were able to revamp their operations and move up.

The arrival of AI may impact the spread of companies in different ways. The immediate concern is that large companies are the only ones that have the resources and the skills to take advantage of AI. However, there are countervailing forces. Large companies may have difficulty changing and lose market share to nimble smaller competitors as suggested by Clayton Christensen (1997).[44] On balance, we suspect that it is the larger, established companies that will be able to take advantage of emerging AI. For example, the surveys by the US Census Bureau report very low adoption of AI in a sample of, mostly, small companies.

What can policymakers do to help spread productive technologies more widely, whether AI or other technologies? One example of successful technology diffusion is the Agricultural Extension Service. Going back to the 1950s until today, agriculture is an industry with one of the highest rates of productivity growth, which has come from the consolidation of small farms and greatly increased mechanization, but also through the spread of technology. The Obama and Biden Administrations also had manufacturing extension programs designed to help technology

[44] Not everyone agrees with Christensen. See for example, Lepore (2014) who argued there was no clear evidence that incumbent firms were adversely impacted by new technologies as they used the advantage of their size to adapt to the changes.

development and diffusion in small companies, but it is not clear how successful that has been. The National Science Foundation, DARPA, and NIST have the potential to contribute to the development of AI for smaller companies. Currently their budgets are being cut, which will reduce their capabilities. Given the current stance of policy, it is likely that large firms in the US will be the ones contributing to productivity from the application of AI to their firms.

Immigration Policy

Most of the immigrants entering the United States in recent years are those without advanced education and this immigration is now being sharply reduced. We do not have a basis for commenting on the likely productivity impact of this shift in policy.

We have discussed the constraints imposed by restrictions on H-IB visas and we pointed out that high-skill immigrants have started many companies. Also, the CEOs of several of the large US tech companies are immigrants. Nvidia, Microsoft, Google, AMD, Tesla and Uber. Easing restrictions on high-skill immigration would likely have a positive impact on US productivity. In contrast, the ongoing cuts in research support and the potential imposition of higher taxes on private universities have the potential to drive leading academics to leave the United States with a negative impact on productivity after a lag.

With respect to H-IB visas, one policy change to consider is to grant the visas to the qualified individuals rather than granting them to the companies. This would encourage mobility in the immigrant workforce and avoid the problem that some companies can pay immigrants below market wages.

Infrastructure Investment

There have been extravagant claims made in the past for the productivity benefits of infrastructure capital, which we disagree with. Nevertheless we judge that this form of capital is productive. Congress has provided funds to repair the interstate highways system, but urban infrastructure is often very weak. An efficient urban public transportation system lowers emissions and allows workers to reduce commute times and increase job opportunities. One problem is the very high cost of some projects. Lower price tags will be needed to justify substantial increases in such infrastructure spending. Cuts to government spending include funding for future infrastructure projects.

Tax Incentives

Productivity policy advocated by the Republican Party has focused on low levels of taxation. The proposed tax cuts currently being considered would allow expensing of physical capital, which is an investment incentive. In general, however, the argument is that lower taxes allow the private sector and workers to make their economic decisions without distortion from the tax system. We agree that tax incentives can impact behavior. It is suggestive that workers in European countries with high tax rates on labor income work fewer hours per year than those in the United States. Average annual full-time hours per worker in the U.S. are 1,804, compared to 1,347 in Germany, 1,501 in France, and 1,440 in Sweden, according to the OECD ("Hours worked" n.d.).

The difficulty with the current push of US tax policy is that there is already a very large federal budget deficit and a sharply rising burden of government debt in relation to GDP. We do not know what it would take to cause a flight from US dollar assets, but dollar interest rates have already risen substantially. It is hard to determine how much of this is associated with inflation concerns and how much reflects a risk premium on the dollar. As we have noted, there is also concern that the current Administration does not appreciate the connection between the saving investment imbalance in the US economy on the one hand and the trade deficit on the other. One major policy push is to increase tariffs to reduce the trade deficit, but another policy push is to reduce taxes, widening the imbalance. Tariffs will raise some revenue, of course, but not enough to have a big impact on the budget deficit.

We do not know of definitive evidence showing the links between taxes, deficits and productivity growth but we note the following. Taxes were increased by President George Bush Senior in the early 1990s and were increased further by President Clinton while productivity growth accelerated sharply after 1995. President George W. Bush lowered taxes in 2001 and 2003 and productivity growth slowed in 2004-5. We are cautious about interpreting this observation. Cutting taxes can impact growth positively for a time through their impact on aggregate demand and excessive tax rates can choke off economic activity. But recent historical experience does not point to a direct link from taxes and productivity in the United States.

VII. Conclusion

The companion papers in The Productivity Institute's Pro-Productivity Policies programme, to which this paper contributes includes analyses for many countries and the lessons from these other countries are important (). Very strikingly, productivity performance has weakened in almost all countries studied. It is possible that the reasons for slow productivity growth are different across the countries, but it seems likely that there are common determinants.

- One possible cause is that the pace of technological advance has slowed, and this is impacting all countries. However, this explanation would suggest the countries at the frontier of productivity would slow down the most, while the countries that are well below the frontier would still be able to keep growing and catch up to the frontier. That does not seem to be the case. The papers for this project revealed that the United States is maintaining solid productivity growth, while Brazil and the European economies, where productivity levels are relatively low, are the ones where productivity growth has been weak or zero. Canada is a striking example where productivity has fallen relative to peer economies despite its market-friendly policies and strong educational performance.
- Another possibility is that governments are regulating their economies more than they used to. Governments can find it hard to resist the temptation to intervene directly in their economies in ways they think are helpful but that hurts productivity. India and China have both introduced more active regulation.
- Globalization has been an important force. It has allowed some economies or industries to grow rapidly, while others have been adversely impacted. Today, globalization seems to be going in reverse. The positive and negative impacts of globalization probably need to be included in an analysis of productivity trends.
- Artificial Intelligence is emerging as a major new technology. How important this turns out to be for productivity and how different economies adapt to it will give new information on the way technological advances impact productivity.

We do not have the answer to the puzzle of global slow productivity growth, but we can learn from bringing together research from different countries to try and find the answers together.

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Appendices

A. A Short History of Federal U.S. Innovation Policy

U.S. government policy has played a substantial role in fostering innovation generally and the development of the information technology sector in particular. This policy has included legislation, court decisions, and executive branch funding. These actions have not only served to foster competition but have also provided foundational public goods and funding for nascent industries. We provide an overview of key policies below.

Legislation

Beginning shortly after the ratification of the Constitution, the U.S. congress created the U.S. patent system, providing a system to ensure inventors had an opportunity to profit from their innovations. The system was updated periodically to ensure its effectiveness, including protection for living organisms (1930), proscription of obvious patents (1952), creation of a patent appeals court (1982), international harmonization (1994), and protection against "patent trolls" (2018).

Congress has also legislated the creation of numerous research institutions to foster basic research unlikely to emerge from the private sector. Among these institutions are "land grant" universities (1862), the National Science Foundation (1950), the Defense Advanced Research Projects Agency (1958), and the National Aeronautics and Space Administration (1958). A host of IT innovations emerged from these institutions, including advances in computing (such as supercomputing techniques developed at the National Labs), communications (such as the protocols used for the internet at DARPA), and other miscellaneous innovations (such as digital image processing at NASA).

Independent agencies to regulate competition have been stood up by Congress as well, including the Federal Communications Commission, the Federal Trade Commission, and the Securities and Exchange Commission. The FCC also governs the distribution of access to radio-wave spectrum with a view to enabling competition and innovation as well. Agencies below the cabinet level have been created with specific functions that support IT innovation. Among these are the National Institute of Science and Technology (successor to the Bureau of Standards) and the National Security Agency.

Table 2 Key U.S. Legislation

Patent Act (1790)	Creates patent system with term of 14 years.
Morill Act (1862)	Creates land grant universities with focus on "agricultural and mechanical arts."
Radio Act (1927)	Regulates spectrum allocation.
NSF Act (1950)	Creates National Science Foundation.
DARPA (1958)	Creates Defense Advanced Research Projects Agency.
NASA Act (1958)	Creates National Air & Space Administration.
Bayh-Dole Act (1980)	Allows patents for federally funded research.
High-Performance Computing Act (1991)	Funding for supercomputing and internet infrastructure.
Telecommunications Act (1996)	Reformed communications sector to encourage competition.
America COMPETES	Funding for scientific research and STEM education.
America Invents (2011)	First-to-file system introduced for patents.
CHIPS and Science Act (2022)	

Court Decisions

Decisions in the Federal court system have fostered competition in the IT sector as well. Among these are decisions that support antitrust enforcement generally (such as *Standard Oil Co. of New Jersey v. United States* (1911)) and those that clarify patent and copyright law (such as *Sony Corp. of America v. Universal City Studios, Inc.* (1984) which provided guidance for copying technologies, *Alice Corp. v. CLS Bank International* (2014), which described the conditions for patenting software). Other court cases modified the structure of specific powerful corporations in the sector to promote competition. Among the companies affected have been IBM, AT&T, Microsoft, Intel, and Facebook.

Table 3 Key U.S. Court Cases

Standard Oil Co. of New Jersey v. United States (1911)	Foundational for antitrust law.
Sears, Roebuck & Co. v. Stiffel Co. (1964)	States cannot provide patent-like protection.
Grinnell Corp. v. Sperry Corp. (1968)	Prevents anti-competitive practices in technology markets.
United States v. IBM (1969-1982)	Forced IBM to unbundle software from hardware.
United States v. Western Electric Co. and AT&T (1974-1982)	Breakup of the Bell System monopoly
Sony Corp. of America v. Universal City Studios, Inc. (1984)	Copying technologies are acceptable if they have non-infringing uses.
Diamond v. Chakrabarty (1980)	Genetically modified organisms can be patented.
Reno v. ACLU (1997)	Struck down portions of Communications Decency Act, allowing freer speech on the worldwide web.
United States v. Microsoft (1998-2001)	Required company to provide application program interface (API) for developers, unbundle browser from operating system.
Federal Trade Commission v. Intel, AMD Inc. v. Intel Corp. (1999-2010)	Addressed anti-competitive behavior.
Alice Corp. v. CLS Bank International (2014)	Guidelines for patenting software and abstract ideas.
MGM Studios Inc. v. Grokster, Ltd. (2005)	Technology providers are liable if they actively induce copyright infringement.
Oracle America, Inc. v. Google LLC (2021)	Fair use for software.
Federal Trade Commission v. Facebook, Inc. (2020 onward)	Antitrust cases against Meta market dominance

Executive Branch Funding Government procurement, particularly military procurement during cold war played a major role in the development of information technology later used in the private sector (See Flamm (1988)). More recently, the CHIPS and Science Act has funded basic research in information technology as well.

B. The Outlook for Further Progress in AI[45]

The rapid introduction of generative AI caught most people by surprise. Machine learning has been around for many years and has made much progress in seeing patterns in large amounts of data. GenAI also uses prediction algorithms but in a different way, to predict the next tokens in a piece of text, based on massive amounts of training on data drawn from the web and other places. Given its current flaws, however, genAI needs continuous development if it is to realize its full potential.

There is an important question about whether recent advances in AI will continue. Possibly, the huge amounts of compute being added at great expense will fail to deal with the problems that exist in AI technology. Or maybe AI will prove to be a transformative technology that raises productivity and disrupts the labor market. The future of AI is very consequential for policymakers. Will AI be transformative and disruptive, or will it turn out to be much less than expected, with development fizzling out and billions of dollars wasted. We do not know the answer, but it is worth looking at how the development of AI has proceeded: what have been the sources of its rapid growth so far.

Given the heavy investment in generative AI models, it is no surprise that they have been getting better over time. For development to continue in the long term, though, it will be necessary to achieve improvements in performance relative to the level of inputs. Without such gains, the returns to investment will decline. Increases in total factor productivity (TFP) in the development process are needed, where economic performance goes up holding input levels constant. Accordingly, we focus below on (a) how innovations in model architecture (the algorithms used for distilling information from data) raise genAI model capabilities without raising training costs, (b) how

[45] This section is an abridged version of the discussion in Baily et al. (2025)

hardware innovations lower the cost of computation, and (c) how richer datasets (with more information per token) can be brought to bear on training.

Model Development Since the introduction of the Transformer, model development has progressed at a blistering pace, including ramping up model scale, dataset size, and compute employed and the introduction of novel model concepts and techniques to increase the efficiency of model training.

The training of genAI models (optimal calibration of its parameters) takes place in two stages: pre-training and fine-tuning. Pre-training produces a broadly applicable "foundation model"; fine-tuning refines the foundation model for a specific application. Efforts early in the wave of genAI improvement that followed the Transformer focused on pre-training, but the escalating cost of making progress in that stage has led researchers to explore improvements in fine-tuning and inference, as discussed below (Zeff 2024).

Advances in performance have come from novel model concepts. Mamba, introduced in 2023, achieved sub-quadratic-time sequence modelling by avoiding the pairwise comparison among tokens used in the attention mechanism that underlies transformer models, meaning that as input texts lengthen, the computational burden increases at a slower pace than the Transformer (Gu and Doa 2024).[46] Small-scale models, with lower computational requirements, have been a focus for some applications as well, such as personal devices and lower resource settings, making LLMs more accessible to the average user.

Pre-training Between 2018 and 2022, a key pre-training tactic in the effort to improve genAI performance was to increase model size. GPT models initially had 117 million parameters in 2018 (GPT-1), then 1.5 billion in 2019 (GPT-2), and a staggering 175 billion in 2020 (GPT-3). Unfortunately, costs typically rise quadratically when parameters are added: each word (token) in the input sequence must be compared to all the others in the attention mechanism. Remarkably, the cost of training a model of a given size was halved approximately every eight months through 2024 (Ho et al. 2024). But, by 2022, the direction of innovation had begun to shift; scaling laws indicated diminishing returns to model size for foundation models.

Fine-tuning As the returns to model size scaling have diminished, researchers have

[46] In particular, Mamba estimates the parameters of a latent state space structure.

begun focusing more attention on fine-tuning foundation models for specific tasks. That is, developers have used domain-specific training data to increase the model's expertise beyond the capabilities of foundation models for narrowly defined questions.

Inference Because of the high volume of inference requests—leading to variable costs in terms of electricity, time, compute, and carbon emissions— techniques to make this step more efficient have arisen.[47] One of the most important innovations in this area has been the *Mixture of Experts (MoE)* approach, an architecture that activates only a subset of model parameters in response to queries (Jacobs et al. 1991). *Pruning* is another inference refinement; here extraneous parameters are removed outright from the model (Cetin et al. 2025). Developers also incorporate *distillation*, a compression-like technique that uses knowledge from large complex models to inform smaller, less costly models (Hinton et al. 2015). *Quantization* reduces the level of accuracy to reduce costs in terms of computation and memory requirements (e.g. moving from 32-bit to 8-bit floating point precision). *Token caching* involves temporarily storing information anticipated to be needed in future inference steps. The recently introduced DeepSeek R1 model from China leverages several of the techniques described above to deliver a substantial performance improvement compared to existing models.

Agents Another direction for progress currently receiving intense attention— distinct from the pre-training/refinement/inference optimization approaches the creation of AI agents. AI agents can remember across tasks (unlike traditional genAI) and they can use more than one AI model to complete tasks. AI agents can make decisions and take actions with little human oversight, which is a potentially powerful advance, but also a concern for those worried about AI getting out of control. If genAI is to have a significant impact on productivity, it will require not only advances in the models but also knock-on innovations, including agents, that are made by businesses to improve their own operations and efficiency.

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[47] After setting a flat fee for access to ChatGPT, OpenAI CEO Sam Altman remarked on *X*, "we are currently losing money on OpenAI pro subscriptions! people use it much more than we expected" (Altman 2025). With the price of the marginal query set to zero, model operators have to confront the possibility that revenue will not cover costs.

Hardware Improvements GenAI model training and inference has massive computational requirements, making ongoing innovation in electronic hardware (and related hardware, such as cooling systems), essential to continued technical advance.

Successive GPUs released by NVIDIA have delivered leaps in AI performance achieved by improvements in the power consumption and computational power of the processing cores. Fortunately for productivity, holding performance constant, the price of GPUs has moved down: In 2007, a $349 GPU provided 0.3 teraflops (TFLOPS) of compute and in 2024, a $299 GPU delivered 15.1 TFLOPS, implying an annual rate of price decline of 24% that persisted for 17 years (Table 4).

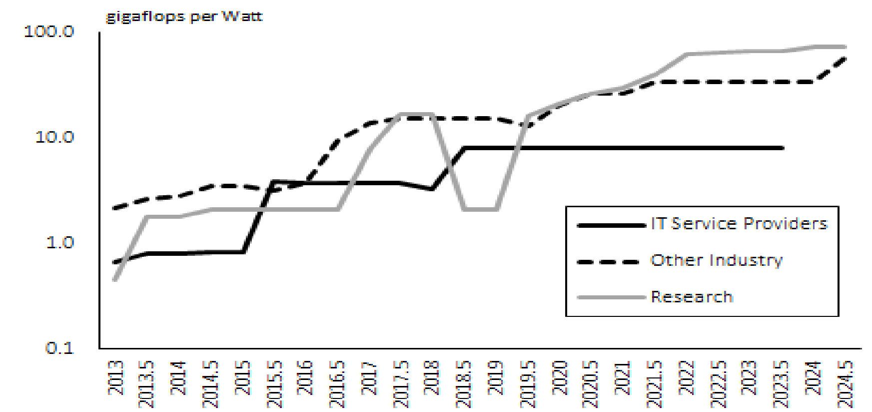
Table 4: Price of GPU Compute

Model	Year	Price	TFLOPS	Price/TFLOP	Transistors
Nvidia GeForce 8800 GT	2007	$349	0.3	$1,163	0.8B
Nvidia GeForce RTX 4060	2024	$299	15.1	$20	18.9B
Pct. change (annual rate)	NA	-1%	23%	-24%	19%

Source: TechPowerUp.

Continuation of this trend of declining computation cost is not guaranteed. Historically, a key contributor to falling costs in the semiconductor industry has been steady miniaturization at the leading edge of the chip industry. From that year forward, the dimensions of these features were reduced far more slowly. The proximal cause of the miniaturization slowdown was the end of a regularity known as "Dennard scaling" whereby power usage was largely unchanged even as more electronic activity was squeezed into the same surface area (Dennard et al. 1974). Consequently, development efforts in the computing sector shifted away from miniaturization and toward power consumption. The energy efficiency at the frontier of research computing has risen roughly 100-fold since 2013 (Figure 12). Given the concerns about the rising energy demands of AI, improvements in energy-efficiency are a crucial determinant of the productivity impact of genAI.

Figure 12: Performance of the Most Energy-Efficient Supercomputers



Note: IT service provider companies contain at least one of these words in the site description: "Internet", "web services", "cloud", "hosting", "IT service", or the names of specific IT service companies. The research group includes both government and industrial research.
Source: Systems included appear on the TOP500 list of most powerful commercially available computer systems and provide information on performance on the HPL benchmark and Watts of power consumed.

Access to Text GenAI models "learn" by adjusting parameters to best represent the content of large amounts of text (and other media), allowing them to estimate the probability that a given word or phrase should appear next in the sequence it generates in response to a prompt. Villalobos et al. (2022) predict that public high-quality text data may become scarce as early as 2026. One approach to mitigating the data constraint is transfer learning, where a model pre-trained with public data by further training using proprietary data.[48] Another potential solution is the use of data augmentation. In one approach, small, localized modifications of the training data can be introduced. Finally, datasets can be augmented via harvesting information collected with sensors, particularly in physical environments such as industrial robots and autonomous vehicles. This approach offers the prospect of a broader domain of use for AI models and further diffusion.

Conclusions on the Sustainability of Progress in GenAI

Given the research efforts being devoted to AI, both in the United States and in other countries, we judge it likely there will be continuing progress made in the next 5-10 years

[48] Cockburn et al. (2018) note that this raises the issue of market structure as a potential constraint on progress in AI.

in the underlying technology. From this perspective we are optimistic about the future of AI. The performance of AI models, however, does not translate directly into productivity growth. Changing production processes and business systems is difficult and expensive. It requires risk, skill and expense and faces pushback from the natural inertia of those who are used to things being done in the traditional ways.

From 2004 to 2024 labor productivity in the nonfarm business sector of the US economy averaged growth of 1.66 percent a year. In 2024 the growth rate was 2.8 percent, leading to the idea that a productivity breakthrough was underway. COVID makes it hard to interpret recent data, but the average growth rate for the three years 2022, 23 and 24 was only 1 percent, so the evidence does not yet show a productivity breakthrough due to AI.