Revolutionary Technologies, Capex Cycles, and the Winding Path to Productivity

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The potential impact of generative AI on the economy is likely to be profound and it bears all the hallmarks of a general-purpose technology

Generative Artificial Intelligence (GenAI) exhibits the defining characteristics of a general-purpose technology (GPT), joining innovations such as steam, railroads, electricity, and modern computing. GenAI could similarly reshape the economy at a foundational level.

Past GPTs have followed a surprisingly similar script, providing a roadmap for how the GenAI era might unfold

AI appears to be following the familiar arc of previous technological revolutions, only faster. In economist Carlota Perez's framework, a breakthrough generates excitement and financial capital floods in to finance the initial buildout. This brings risks of speculation, overinvestment, and market dislocations. Eventually, the financing cycle turns but leaves behind expanded capacity and lower usage costs. Production capital then drives broader adoption, integration, and productivity gains.

The AI buildout is moving at an extraordinary pace, significantly outpacing the largest capex booms in history

AI is in the frenzy phase of the installation period, marked by an enormous buildout of the physical infrastructure needed to support its growing use. This is generating substantial demand for the physical inputs and specialized labor needed to bring AI capacity online. Hyperscaler capex could approach 3% of GDP by 2027, while AI-related stocks now represent nearly half of the S&P 500's market capitalization, as expectations for future AI profits may have run well ahead of what current adoption and commercial returns can support.

History suggests the productivity payoff only emerges after the speculative frenzy phase has ended. The boom-bust cycle is a feature, not a bug

AI's productivity benefits are likely to be significant, as recent microstudies suggest, but they have not yet appeared clearly in economy-wide data. This is not unique to AI, but reflects a common pattern known as the productivity "J-curve." Adopting new technologies is initially costly as firms learn how best to use them and invest heavily in intangible and organizational capital before eventually reaping the benefits.

Along the way, there will be winners and losers

AI will generate significant value, but there is a serious risk that the gains will not be evenly distributed. The impact on employment will depend on the balance between the work AI displaces and the new work it creates, which is difficult to predict. We are more confident that AI will reinforce the historical tendency of automation to shift income away from labor and toward capital, potentially widening inequality.

AI as a general-purpose technology

General-purpose technologies (GPTs) are distinguished from more routine breakthroughs by their wide-ranging scope and their capacity to completely redefine economies. They do more than solve a singular problem. Bresnahan and Trajtenberg (1995) identify three defining characteristics of GPTs: they apply broadly across sectors, improve continuously over time, and generate complementary innovations that reinforce and expand the importance of the core technology.

Earlier GPTs include steam power, electricity, and information technology. Each did more than make existing activities more efficient: they reorganized production and created entirely new economic possibilities, from the modern factory and mass production to software, the internet, and the digital economy.

AI fits this same mold. It is broadly applicable across knowledge work, while its capabilities continue to improve rapidly and its costs decline amid intense competition. Perhaps more importantly, AI creates a feedback loop of complementary innovation. As firms find new applications for the technology, its economic value rises, encouraging further investment and experimentation. Those advances, in turn, make possible still more applications.

Like previous GPTs, the transformative potential of AI will be difficult to anticipate, and future use cases will likely run well ahead of what businesses currently imagine. Early commercial applications of steam, electricity, and computing revealed only a fraction of their eventual capabilities. Steam was initially used to pump water from mines, electricity for lighting and stationary power, and computers for numerical calculation. Later uses of steam in railways, electricity in appliances and mass production, and computers in networks and software were difficult to imagine at the outset. AI appears to be following a similar pattern. Early use cases centered on chatbots and coding assistance, but these are already broadening into agentic workflows and increasingly autonomous processes.

Finance and physical investment also play a critical role in the diffusion of GPTs. Economist Carlota Perez characterized the techno-financial cycle that often accompanies major technological revolutions. It begins with a breakthrough innovation, or "irruption," followed by a period of frenzy, when excitement mobilizes financial capital around the new technology. This funds the infrastructure needed for the technology to spread, but can also lead to speculation and overinvestment. Eventually, the financial cycle turns. Some investors suffer losses, but much of the infrastructure remains, leaving behind expanded capacity and lower usage costs. These improved economics support broader adoption and more intensive use by firms. In Perez's framework, this is when production capital begins to supersede financial capital and the technology becomes embedded in economic activity.

GPTs represent critical junctures in economic development and are among the most powerful forces for raising living standards. But the initial breakthrough, the investment needed to diffuse it, and the eventual productivity gains need not happen at the same time.

From breakthrough to boom

The technologies underpinning today's AI boom emerged gradually rather than suddenly and were the product of decades of research that intensified over the last decade and a half. Advances in computing were as important as advances in the underlying machine learning theory and algorithms. In fact, much of the theory underlying modern AI is fairly old. But increased data availability and computing power made recent breakthroughs possible at scale. The Transformer architecture was released in 2017, but it would take the release of ChatGPT in late 2022 for AI to truly "irrupt" into the broader economy and become visible.

Why was ChatGPT particularly important? It represented a certain consumerization of AI. What had been abstract or academic was suddenly available for anyone to interact with directly, expanding what people thought was possible.

History suggests that major technological breakthroughs often produce exactly this kind of rapid reassessment of future economic opportunities. Going back to our canonical list of GPTs, the contemporaneous accounts of their transformative impact are striking. Nineteenth-century observers believed railways would lead to the "annihilation of space and time," with distant places seeming suddenly nearby. Electricity promised more than power but a force thought capable of animating life itself, with Popular Science Monthly writing in 1891 that the "miracles of olden time seem poor and commonplace" next to electricity. Modern computing brought predictions of the disappearance of the office worker, while the internet promised the "death of distance." Exciting stuff for sure, and often exaggerated, but also practically important in spurring investment and innovation.

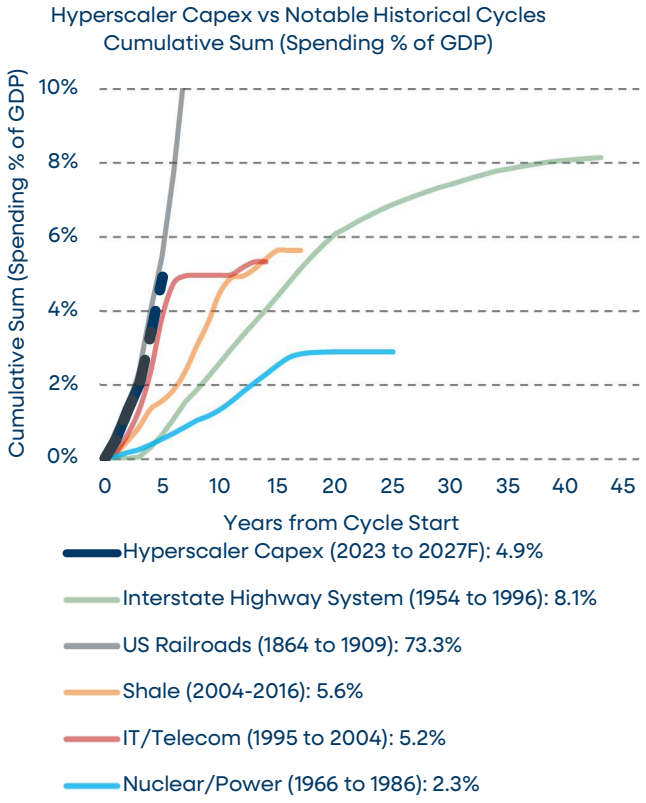
AI is capturing the popular imagination in much the same way. It also threatens to automate something that seemed relatively impervious to the march of the machines: human cognition. The potential therefore seems almost limitless and nominally bounded by the economy itself. Little surprise that both Anthropic and SpaceX have put their total addressable markets at close to $30 trillion, or nearly 100% of U.S. nominal GDP. Believe these claims or not, the message is persuasive to many investors.

This is a common pattern during periods of technological revolution, when investors finance a massive buildout with uncertain knowledge of the eventual payoff. And it can be fully consistent with rational beliefs. A rich academic literature developed around the dot-com bubble and earlier technological booms makes this point, including Pástor and Veronesi (2009), Li (2007), and DeMarzo, Kaniel, and Kremer (2007). Taken together, these papers show how uncertainty and learning around a new technology can produce bubble-like valuations, investment booms, and even eventual overinvestment without requiring investors to have been obviously irrational at the outset.

AI is following this script: its financial and physical impact is arriving long before its ultimate economic payoff is clear.

The current AI boom

Figure 1: Hyperscaler capex is rising rapidly, significantly outpacing the largest capex booms in history

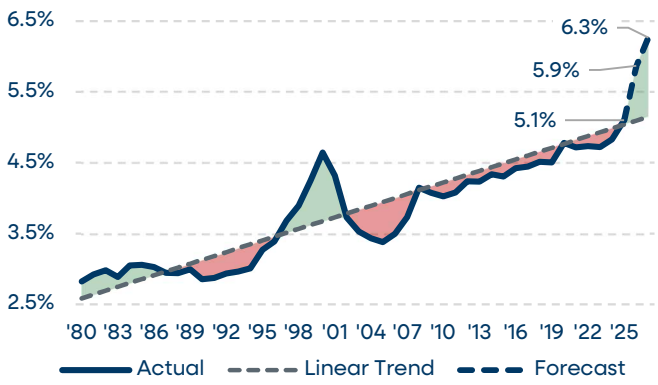


Source: BEA, Bloomberg, BLS, Fin Moorhouse, Government Agency Reports, Penn World Table, PNC
Note: Railroad capex series constructed by PNC using data from Ulmer (1954), Fishlow (1965), Gallman and Rhode (2019), and annual miles of track laid from FRED (St. Louis Fed)
Forecast values for the current AI infrastructure cycle are based on consensus hyperscaler capex estimates and PNC forecasts for nominal GDP for 2026-2028. Series for IT/Telecom, Shale, and Nuclear/Power capex cycles estimated from change in aggregate sectoral investment relative to the cycle starts, excluding years with a relative decrease in investment

The speed and scale of the current investment cycle are extraordinary by historical standards. Hyperscaler capital expenditures are projected to approach 3% of GDP by 2027, placing the current AI buildout alongside some of the largest infrastructure booms in modern economic history. In fact, it will soon surpass the telecom expansion of the 1990s. At the same time, AI-related firms have become a dominant force within equity markets,

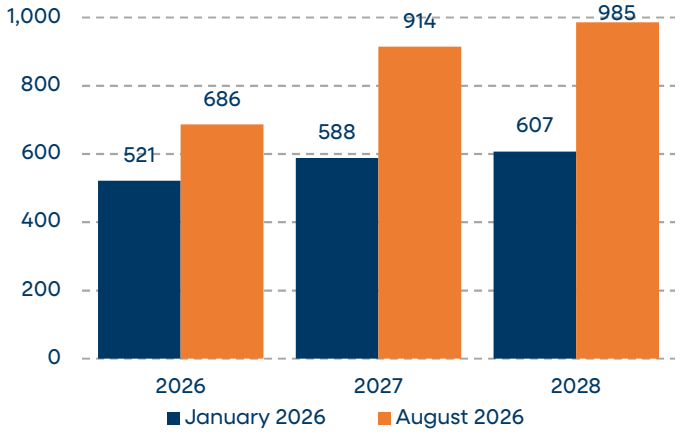
reflecting investor expectations that AI will become one of the most important technologies of the coming decade.

Figure 2: Broad tech capex (% nominal GDP)



Sources: BEA, PNC

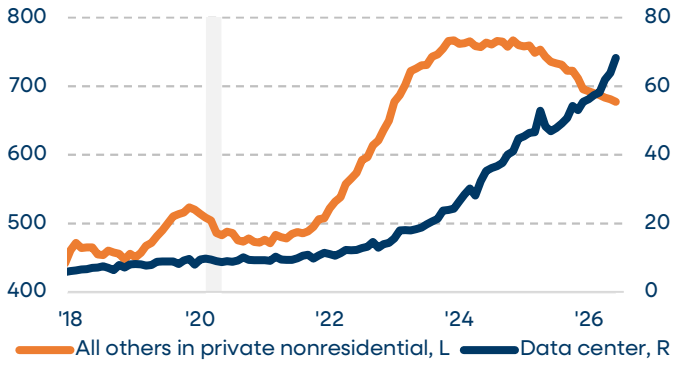
Figure 3: Hyperscaler capex guidance (billions of dollars)



Sources: Bloomberg, PNC
Note: Sum of capex guidance from Amazon, Google, Microsoft, Meta, and Oracle.

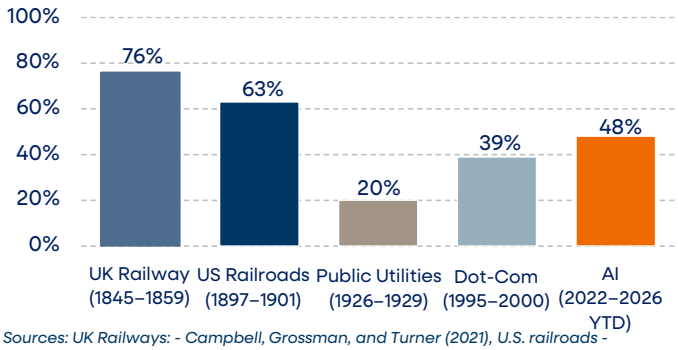
Even compared with previous infrastructure booms, the current cycle exhibits a striking degree of concentration. Prominent technology companies account for a disproportionate share of investment spending and are also helping to finance it, bearing or underwriting downstream demand and credit risk and putting their immense balance sheets to work. The enormous capital needs have led to greater reliance on debt financing and corporate bond issuance. Meanwhile, non-AI capex has weakened and may increasingly be crowded out by AI's demand for capital. Together, these forces amplify concentration risks across capital markets and the broader economy.

Figure 4: Private construction spending (SAAR, $bn)



Sources: Census, PNC

Figure 5: Peak sector market-cap share across major technology booms (% of total market cap)



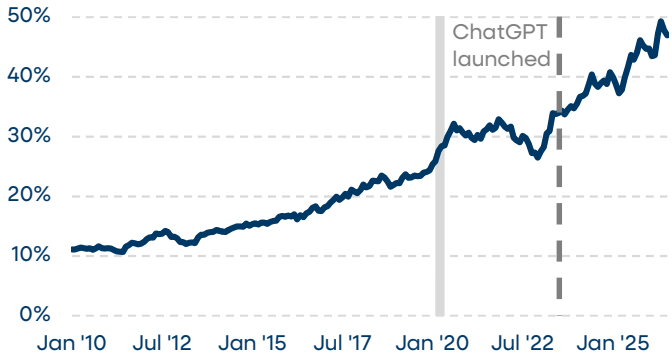
Sources: UK Railways: - Campbell, Grossman, and Turner (2021), U.S. railroads - Dimson, Marsh & Staunton (2015) and Ritter (2012); public utilities - McGrattan & Prescott (2003), dot-com and AI - Bloomberg.

The technology may be digital, but its immediate economic effects are physical. AI compute demand was initially dominated by model training, but that is changing as adoption broadens and token usage soars. Inference is becoming a larger and more persistent source of demand because compute is required every time a model is used. This is fueling a historic data-center investment boom, with chips accounting for roughly half of construction costs and data centers requiring enormous amounts of electricity.

The key risk is that power infrastructure does not scale as quickly as compute demand. Hyperscalers may have the capital to achieve their ambitions, but the electrical grid could increasingly become the binding constraint.

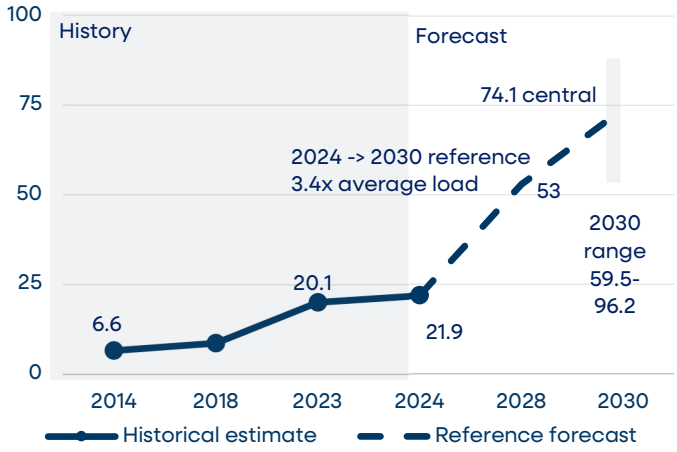
Semiconductor supply can respond relatively quickly compared with the time required to build generation, transmission, and other supporting infrastructure.

Figure 6: Broad AI-linked firms' share of S&P 500 market cap



Sources: Bloomberg, PNC

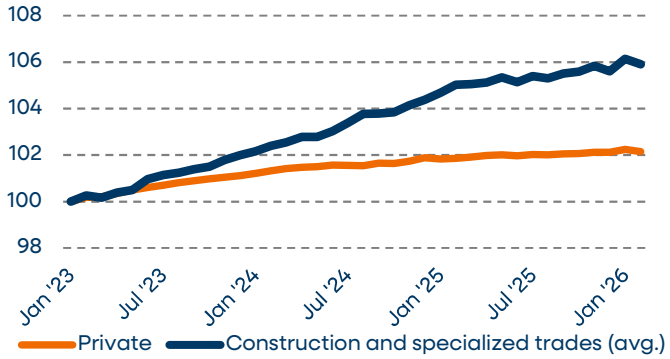
Figure 7: U.S. data-center electricity demand (GW)



Sources: LBNL, PNC
Note: Annual electricity consumption expressed as equivalent average load, calculated as TWh divided by 8.76. Historical values are modeled estimates; the 2030 range reflects compounded-uncertainty scenarios

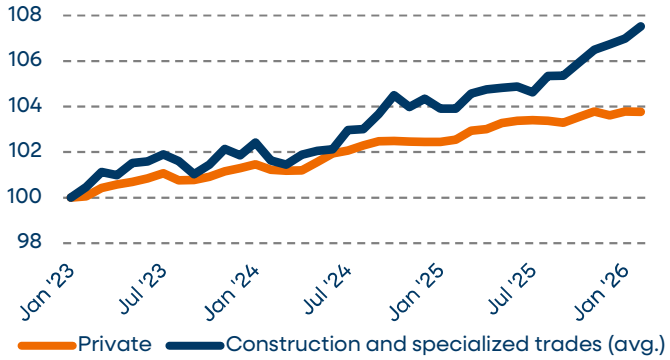
Popular discourse around AI has focused on its potential to displace workers, but the irony is that shortages of skilled trade labor could become a meaningful constraint on the buildout itself. Data-center construction requires electricians, plumbers, pipefitters, and other specialized trades in addition to more general construction labor. This demand has helped fuel strong construction employment and real wage growth since 2023, outpacing the broader private labor market. Apprenticeships are rising, but training takes years. Given the speed of the buildout, labor constraints will likely persist even if semiconductor supply improves.

Figure 8: Indexed employment (Jan 2023=100) for construction and specialized trades



Sources: BLS, PNC

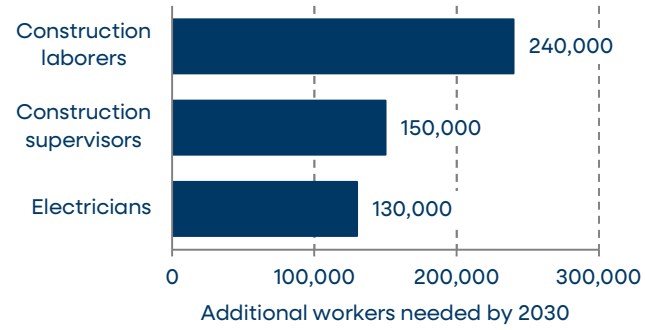
Figure 9: Indexed real wages (Jan 2023=100) for construction and specialized trades



Sources: BLS, PNC

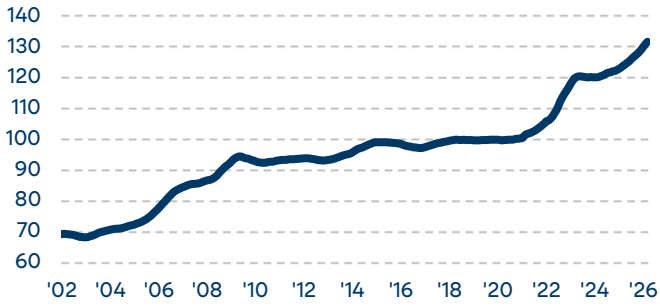
The intensely physical nature of the AI buildout means the technology could be inflationary before its productivity gains ultimately become disinflationary. Retail electricity prices have risen sharply, as have prices for semiconductors and electrical equipment. These pressures could matter for monetary policy, particularly while inflation remains elevated. At Jackson Hole, Fed Chair Kevin Warsh emphasized both the extraordinary strength of AI-related investment and the uncertainty surrounding the timing of its productivity gains. The investment boom is happening now, while the productivity gains will take time to materialize. In the interim, the buildout itself can put upward pressure on prices.

Figure 10: AI buildout will require far more skilled trades labor



Sources: McKinsey, PNC

Figure 11: Retail electricity prices have surged



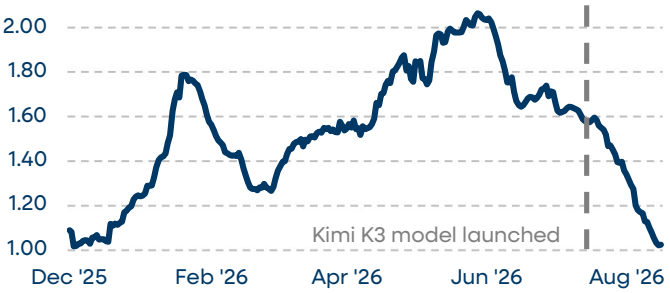
Sources: EIA, PNC
Note: The chart shows the average retail price of electricity indexed to 2019 at 100. A twelve-month rolling average is used to smooth seasonal variation.

At the same time, rising input costs are coinciding with arguably weaker pricing power for firms providing AI services. Competition, including from lower-cost open-weight Chinese models, is pushing inference prices lower even as the cost of providing it remains substantial. LLM token prices are therefore one area where inflation has remained notably contained. The problem is that the cost of running these models has not fallen nearly as quickly as the prices being charged for them. That puts pressure on the margins of hyperscalers and frontier labs. If it continues, investors may start to question whether the enormous amount being spent on AI can ultimately be supported by the revenues the technology generates.

Figure 12: Semiconductor and electric component manufacturing producer price inflation (% chg., y/y)

Sources: BLS, PNC

Figure 13: LLM token prices have fallen sharply as cheaper open-weight models have increased competitive pressure



Sources: Bloomberg, PNC
Note: Chart plots the Silicon Data LLM Token Expenditure Index, a benchmark of the effective cost of using large language models measured in price per million tokens.

Bubbles and their productive afterlife

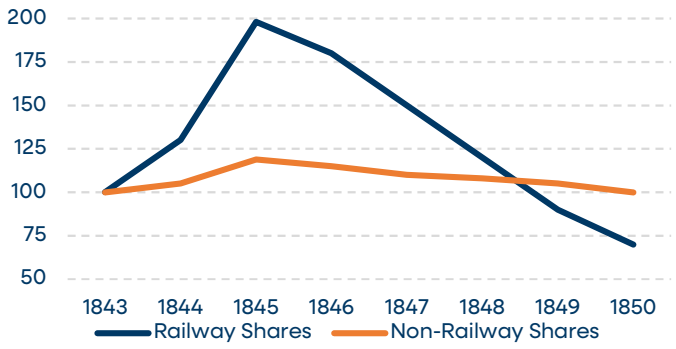
Speculative excess and overbuilding are recurring features of GPT booms – think the railroad booms of the 19th century, the euphoria around automobiles and electricity a century ago, and the internet bubble of the late 1990s. The eventual financial losses can be severe.

But bubbles and busts often have a productive afterlife when the infrastructure they leave behind lowers usage costs.

An early example is Britain's railway mania of the 1840s. The success of the first commercial railways galvanized confidence in the technology. Interest rates were low, while a growing pool of middle-class investors was venturing more heavily into equity markets. In an echo of

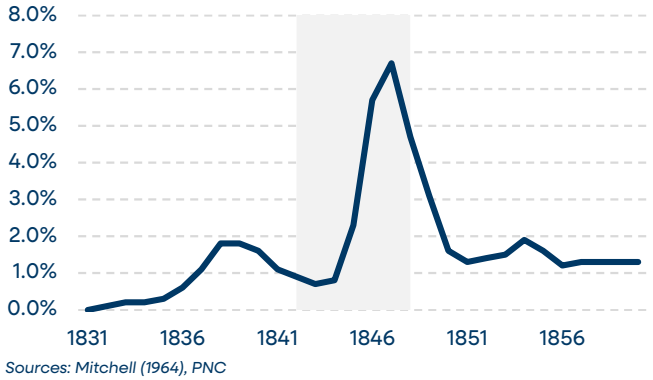
conditions today, leverage magnified the boom: investors could subscribe to railway schemes by paying only 10% upfront, while remaining liable for future capital calls. Railway shares roughly doubled between 1843 and 1845, helping fuel a sharp rise in investment. Rising policy rates and the credit crisis of 1847 eventually spoiled the party. By 1850, railway shares had lost roughly two-thirds of their peak value and investment had collapsed. Yet the boom left Britain with a much larger network that lowered transport costs, shortened travel times, integrated markets, and supported broader industrialization. The productivity payoff would peak in 1870s, thirty years after the boom.

Figure 14: Growth in UK railway share values during the mania (1843 = 100)



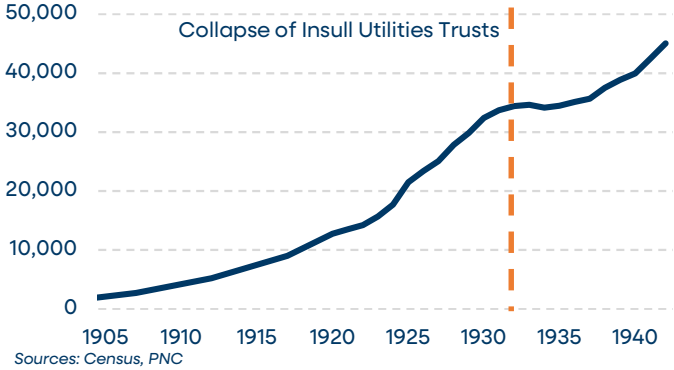
Sources: Campbell (2013), PNC

Figure 15: Gross UK railway capital formation ex. land (% of national income)



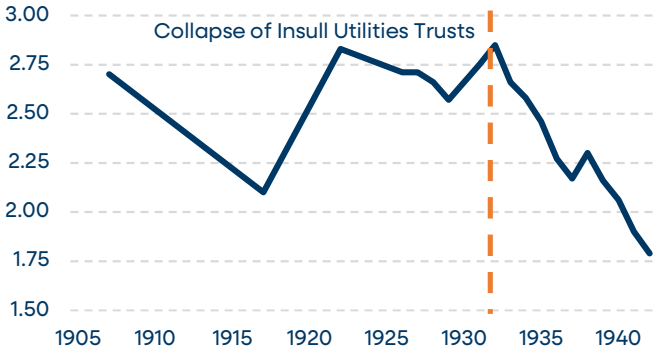
Sources: Mitchell (1964), PNC

Figure 16: Electricity utility installed generating capacity (thousand kilowatts)



Sources: Census, PNC

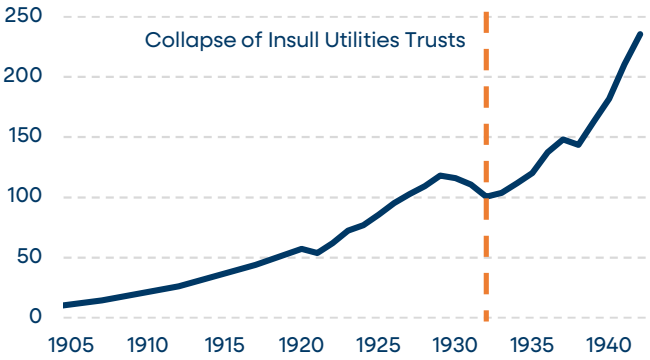
Figure 17: Average electricity prices of all services (cents per kilowatt-hour)



Sources: Census, PNC

Something similar happened with electricity. As miraculous as the new technology was, more ho-hum innovation in business organization and corporate finance was needed to truly drive mass adoption. Samuel Insull, a protégé of Edison, helped provide it by consolidating local operators, achieving greater scale, improving utilization, and driving down rates. His holding-company structure allowed him to raise massive amounts of capital but also generated substantial leverage. A relatively small equity base controlled a much larger utility empire through layers of debt and preferred stock placed above regulated operating companies.

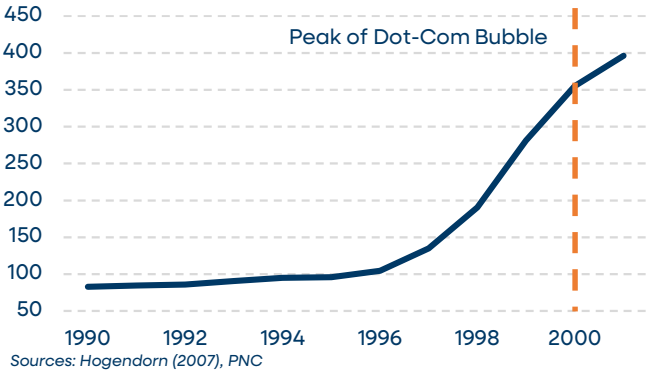
Figure 18: Total electric energy use (billion kilowatt-hours)



Sources: Census, PNC

The Great Depression exposed the fragility of that structure as weakening electricity demand coincided with collapsing security prices. Insull's holding companies collapsed in 1932. But the excess capacity left behind by the buildout helped drive down electricity prices and supported a sharp rebound in electricity use. Along with that came further experimentation. Field (2011) argues that the 1930s were an unusually inventive period, setting the stage for the full productivity payoff to arrive in the 1950s.

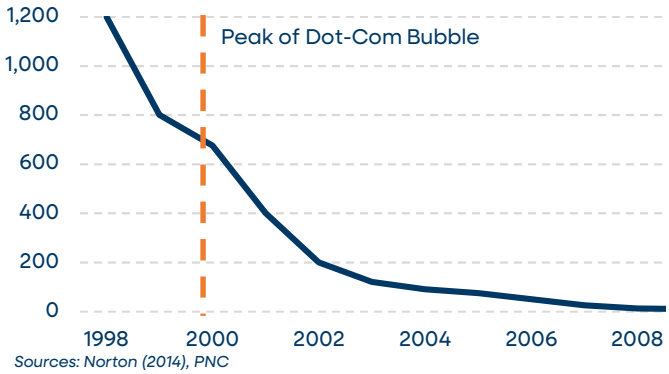
Figure 19: Total national long-haul network route miles (thousands)



Sources: Hogendorn (2007), PNC

Unsurprisingly, the most familiar modern analogue is the late-1990s dot-com bubble and telecom buildout. The euphoria was grounded in the growing ubiquity of the PC, the emergence of the commercial internet, and tentative signs of an information technology-driven productivity boom, at least anecdotally. Equity valuations took off, lowering the cost of capital, while the Telecommunications Act of 1996 opened previously segmented telecom markets to competition and added further momentum to the network buildout. The Nasdaq rose 86% in 1999 before peaking in March 2000 and falling 77% by October 2002.

Figure 20: Internet transit prices (dollars per megabits per second)

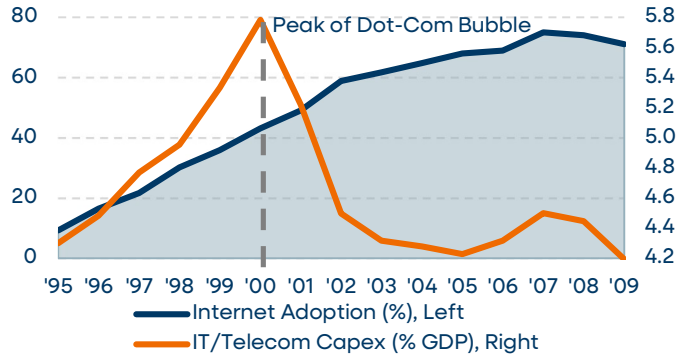


Sources: Norton (2014), PNC

Much of that capital went into physical infrastructure. U.S. long-haul network route miles increased from roughly 83,000 in 1990 to more than 350,000 by 2000 (Hogendorn, 2007). Demand for data continued to grow quickly, but not quickly enough to justify the valuations and capacity plans of many telecom firms. Bankruptcies followed in 2001–02. The buildout plateaued, but internet prices continued to plummet as traffic rose. The next generation of digital businesses was built on this cheap and abundant capacity, and those same firms now play a critical role in the AI buildout.

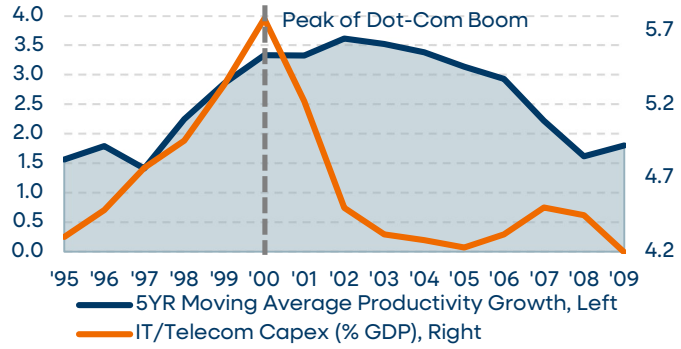
What do these historical vignettes suggest for AI? Overbuilding is the norm rather than the exception, especially under a cloud of uncertainty, competition, and lengthy time-to-build that makes it difficult to know precisely how much capacity will be needed or to anticipate future technological innovations that could make its use more efficient. Some investors may lose money and some projects may prove uneconomic, but the surviving infrastructure can still leave the economy with cheaper compute and facilitate the broader transformation around AI.

Figure 21: Internet adoption continued well past the capex bust...



Sources: GenAI Adoption Tracker (RPS), BEA, PNC

Figure 22: ...as did productivity growth



Sources: BEA, BLS, PNC

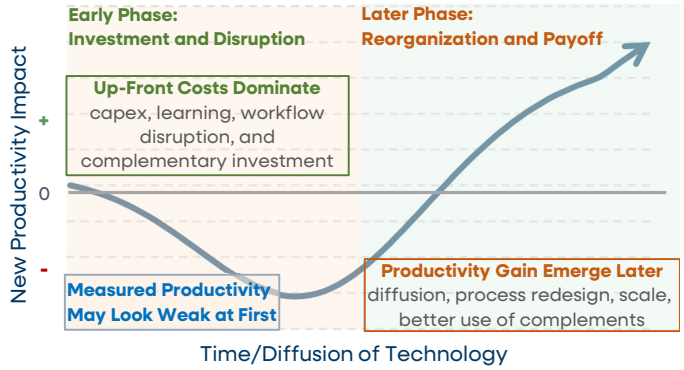
Table 1: From invention to productivity payoff, historical GPT cycles

	Steam (Britain)	Electricity	ICT	AI (so far)
Core invention	1769	1880s	1970s	2017–22
Speculative frenzy	Railway mania (1840s)	Insull utilities (1920s)	Dot-com bubble (1990s)	Hyperscaler capex boom (2023–?)
Crash	1847-50	1929–32	2000–02	?
Peak productivity payoff	1870s+	1950s	2000s	?
Lag (years)	~100	~70	~30	?
Key complement	Factories, rail, skills	Factory redesign, unit drives	Process re-platforming, supply chains	Data quality, workflow redesign, governance

Sources: BEA, Census, Crafts (2004), Gordon (2016), Perez (2002), Schmid (2025), PNC

All the (necessary) boring stuff in between invention and payoff

Figure 23: The productivity J-curve



Sources: Brynjolfsson, Rock, and Syverson (2019), PNC

Physical infrastructure is only half the story. Firms must also make significant investments in intangible capital to put the technology to productive use. This is the frustrating part of adoption and helps explain why GPTs are not immediately transformative. New skills must be developed, organizations redesigned, and industry standards established before the technology can be fully integrated into production. These investments can initially consume resources without generating much measured output, producing what Brynjolfsson, Rock, and Syverson (2021) call the "productivity J-curve." There is therefore typically a multi-decade delay between the onset of a GPT and the realization of measurable aggregate productivity gains in the national accounts.

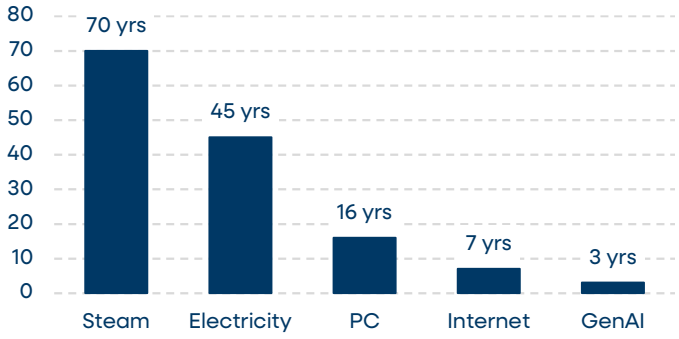
James Watt's introduction of the modern, commercially viable steam engine in 1769 did not yield an immediate economic acceleration. Steam power contributed very little to growth before 1830 and did not reach its peak macroeconomic impact until roughly a century after its initial invention (Crafts, 2004).

Electricity diffused at a similarly slow pace. Thomas Edison pioneered commercial electric lighting in the 1870s and 1880s, but productivity growth did not take off until the 1920s. Existing steam-driven factories were organized around a central power source, with shafts and belts running through multistory buildings. Simply retrofitting

these structures with centralized dynamos failed to fully harness electricity's potential (David, 1990). Falling utility costs and experimentation eventually led factories to reorganize around "unit drives," with individual electric motors powering individual machines.

Information technology diffused relatively quickly by comparison, but still confounded contemporary observers through its delayed appearance in the hard data. Robert Solow famously stated in 1987 that "[y]ou can see the computer age everywhere but in the productivity statistics," while David's (1990) analogy with the dynamo argued for patience. The world's first commercially available microprocessor, the Intel 4004, was released in 1971, and IBM followed with the desktop PC in 1981, but productivity growth would not meaningfully accelerate until the mid-1990s.

Figure 24: Years until 50% adoption rate

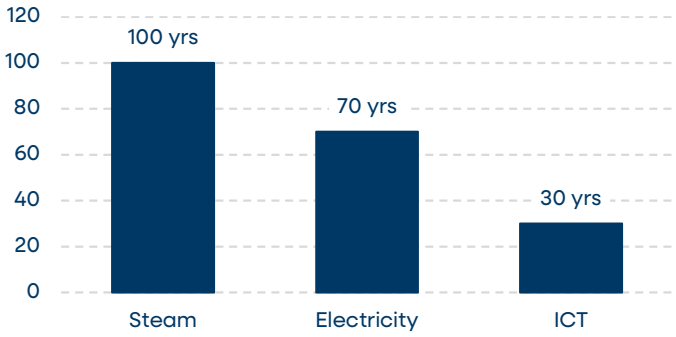


Sources: Crafts (2004), Census, GenAI Adoption Tracker (RPS), PNC

Note: Steam adoption is measured as a share of total power since 1760. Electricity is measured as the share of dwelling units with electric service since 1880. PC, internet, and GenAI adoption are based on individual self-reported usage relative to the first mass-market product (IBM PC in 1981, commercial internet in 1995, and ChatGPT in 2022).

The experience with computers also shows how much of the investment needed to make a GPT productive can be hidden from view. Firms had to reorganize work around information and make large complementary investments in intangible organizational capital. Brynjolfsson, Hitt, and Yang (2002) found that an incremental dollar of IT investment generated a much larger increase in firm market value than a similar investment in other tangible assets. Their interpretation was that measured IT spending came bundled with substantial investments in organizational capital that were not properly captured in official statistics but were necessary to realize the technology's value.

Figure 25: Approximate years to peak productivity impulse from core commercial invention

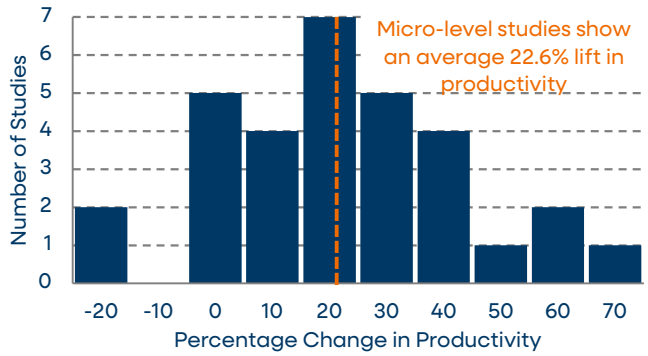


Sources: Crafts (2004), BLS, PNC

Note: ICT stands for information and communication technology.

AI is spreading much faster. Generative AI crossed the 50% adoption threshold in just three years, compared with seven for the internet and 16 for the PC. Electricity and steam spread even more slowly, with diffusion better measured in generations than years. That does not mean diffusion is complete. Kalyani et al. (2025) find that it can take more than 50 years for new technologies to spread geographically.

Figure 26: Distribution of AI labor productivity estimates

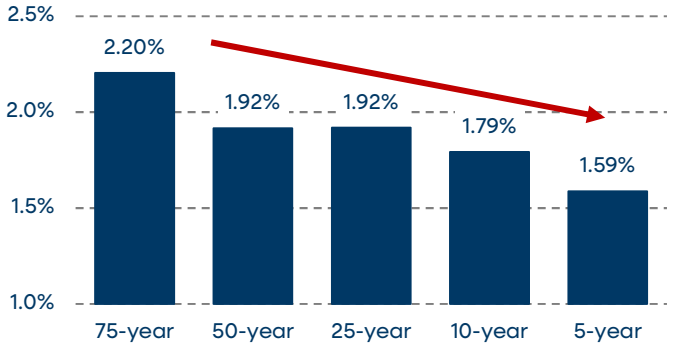


Sources: Various papers, PNC

But using AI is not the same as reorganizing production around it. Firms are still figuring out how to redesign workflows, where humans belong in the loop, what governance should look like, and even how success should be evaluated. The upshot of faster adoption may

be an earlier confrontation with the costs of implementation, while the delay in realizing measurable productivity gains remains. GenAI could therefore produce a steeper J-curve than previous GPTs, even if it ends up being a shorter one. Improvements in individual tasks may also run into bottlenecks elsewhere in the workflow, preventing firms from realizing the full productivity gains. More broadly, weak links elsewhere in the economy could mean that AI's aggregate punch is less forceful than its task-level performance might suggest.

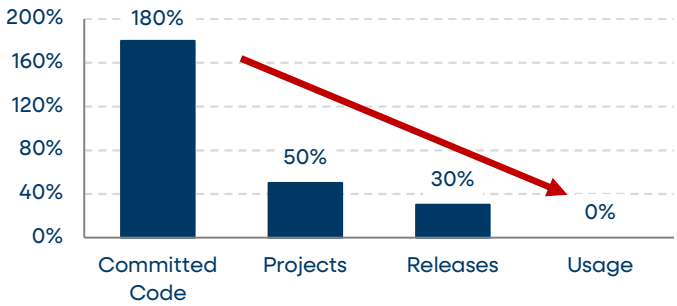
Figure 27: Annual labor productivity growth: trailing average by horizon



Sources: SF Fed, PNC

So far, the data seem to agree with this. Micro-level studies of well-defined but narrow tasks show large productivity gains. At the same time, there has been little evidence of an AI-driven pickup in broader productivity growth.

Figure 28: Large coding gains have yet to translate into usage



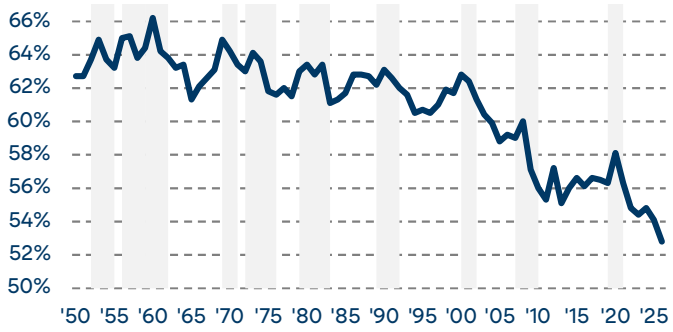
Sources: Demirer, Musolff, and Yang (2026), PNC
Note: Percent changes are estimated increases relative to developers' pre-tool adoption baseline. Projects refers to distinct repositories touched; usage reflects no increase in app usage/download proxies within three months of launch.

Demirer, Musolff, and Yang (2026) provide a particularly illuminating example. The paper traces productivity gains through the software production hierarchy and shows how they fade as output moves closer to actual usage and revenue. AI tools led to much more committed code, but the gains became progressively smaller across projects and releases, with no increase in end-user engagement. In short, writing more code is not the same as shipping more software, which is still a long way from guaranteeing that anyone actually uses it. AI may seem extremely visible within firms while having a weaker impact on revenue and barely registering in the broader macroeconomy. The micro-macro productivity paradox should be resolved over time as firms work their way through the J-curve.

Brave new (unequal) world

The distributional consequences of AI are clearer than its employment effects. Like previous waves of automation, AI should reduce labor's share of income by shifting more tasks from workers toward capital, software, and machines.

Figure 29: Labor share of income has been in long-term decline

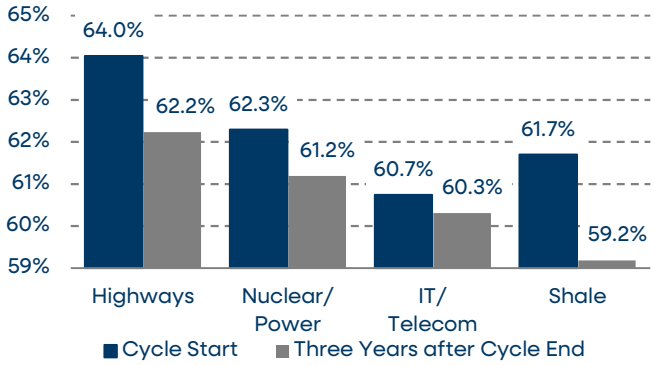


Sources: *BLS, PNC*

The complementary investments required to make AI productive – data infrastructure, workflow redesign, organizational change, and proprietary know-how – are costly, cumulative, and difficult to replicate. Larger firms that can spread the immense fixed costs of adoption across a broader revenue base and build on their existing organizational capital will benefit the most. This may

reinforce market concentration. Capital owners and superstar firms may capture much of the surplus generated by AI-driven productivity gains.

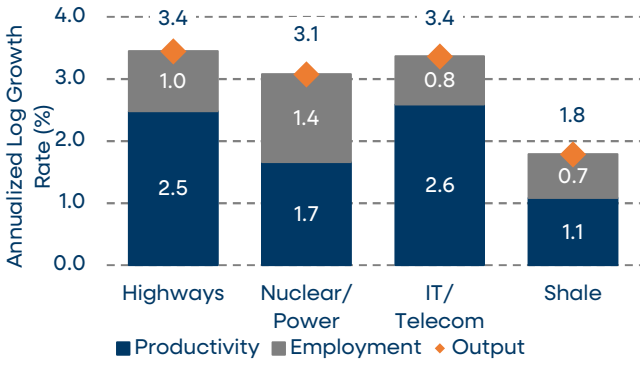
Figure 30: Labor share of income declined over past capex cycles...



Sources: BEA, BLS, PNC

Right now, the greatest debate and disagreement centers on AI's impact on employment. It's also where we have the least conviction. AI is likely to displace some jobs before it leads to the creation of new tasks and markets that offset those losses. This is the tension between the displacement and reinstatement effects of new technologies. The direction employment moves will depend on the balance between the two, although displacement naturally resonates far more strongly. Indeed, it is much easier to contemplate the jobs and industries that AI could disrupt than to imagine the new types of work it could create.

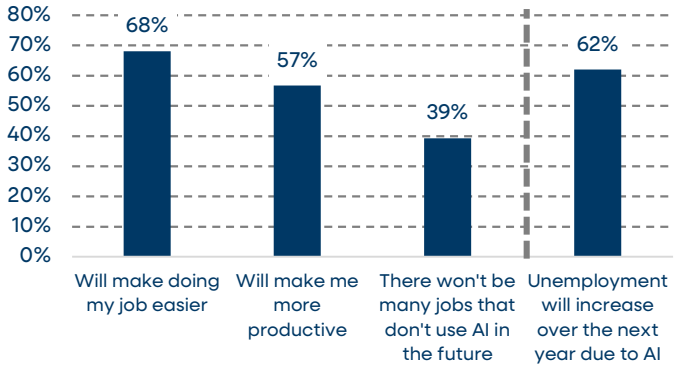
Figure 31: ...but output growth exceeded productivity growth, so employment still grew



Sources: BEA, BLS, PNC

Since we've used history as a guide in our exploration of AI, what does it have to say about this? Fortunately, the verdict is positive: despite persistent fears around technological change, the economy ultimately emerged stronger and with higher employment. The caution is that not everyone benefited, and inequality could rise even without a slowdown in employment.

Figure 32: Workers believe AI will increase productivity and unemployment



Sources: NY Fed, PNC

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