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CHAPTER

Advancing Economic Participation in the AI Era: A Private- and Public-Sector Agenda

by Glenn Hubbard and Luke Pardue

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AUTHORS

Glenn Hubbard[*] and Luke Pardue[**]

ABSTRACT

Ongoing advances in artificial intelligence are poised to reshape the US economy at a scale and speed the country has not experienced from previous advances in technology. These advances come with the promise of increased prosperity, but they will also come with large-scale disruption to existing forms of economic activity. The scope and pace of that disruption is uncertain; accordingly, adaptation by firms, workers, or public policy is in part a risk management problem. This paper lays out an agenda for a private- and public-sector response that ensures Americans are prepared for and connected to new economic opportunities amid this transition and to a new long-run structure of the economy and labor markets. This agenda outlines steps for workers and firms to navigate the AI transition, labor market policies that connect people to the rapidly changing economy, and fiscal policies that can adapt to shifting forms of economic activity and provide adequate public resources to fund policy support.

[*] Dean Emeritus and Russell L. Carson Professor of Finance and Economics, Columbia Business School; Professor of Economics, Columbia University.
[**] Policy Director, Aspen Economic Strategy Group.

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Introduction

The capabilities and applications of artificial intelligence (AI) are growing at a rapid pace, coupled with historic levels of private spending on energy and computing infrastructure aimed at further increasing its development and adoption.[1] Many business applications of AI are already raising worker productivity; this phenomenon has been documented across different industries, from software and information technology to manufacturing (Cui et al. 2025; McElheran et al. 2025). These trends are poised to accelerate for the foreseeable future, setting the stage for a dramatic transformation of the US economy.

The rise of AI will likely bring economic benefits over the long run, including higher aggregate income and wealth. However, the gains may be unevenly distributed, and the path to this end state will involve a disruptive transition. As the economic value of certain work falls and new opportunities take time to emerge, many Americans might not benefit immediately from the changes brought about by this technology.

While economists often focus on the long-term net benefits of structural changes to the economy, failing to consider the effects during the transition period can lead to populist pushback, thereby putting steady-state economic gains at risk. An instructive example can be seen in geographically concentrated labor market disruptions resulting from China's rise in manufacturing trade, which have driven widespread skepticism of the benefits of openness and free trade.

We outline an approach for the private and public sectors to wisely manage both the transition period and the long run for an economy reshaped by AI. During the transition, firms should take a mindful approach to worker training, career development, and job displacement. Such an approach, aimed at fostering maximum economic participation and reducing fear of AI, aligns with the long-term interests of private companies. Workers should also proactively identify new opportunities to develop economically valuable skills.

The public policy response should modernize the country's social insurance landscape to provide temporary income support to out-of-work adults while at the same time reconnecting workers to new opportunities. Policymakers must also improve workforce training programs for this future state, investing in educational institutions like community colleges that will prepare workers with economically valuable skills. Finally, AI-driven shifts in economic activity should prompt consideration of a different tax structure. That structure should also be flexible to different shapes economic activity may take in the future, and it should raise revenue in a way that encourages domestic savings, investment, and growth.

[1] See, for instance, Financial Times 2026.

1. Principles to Guide Private and Public Action

We begin with four broad principles, informed by data and economic research, to guide our proposal.

1. Understanding that AI's continuing progress (and disruptions) will be both fast and uneven is important.

AI researchers, technology firms, the policy community, and commentators have laid out visions for different types of AI. For example, "narrow AI" refers to systems capable of completing tasks, such as generating text or images, including generative AI models in use currently. "Artificial General Intelligence" (AGI) refers to context-aware systems that possess broad, human-level intelligence (Stanford HAI 2022). We take the path of both together in describe reactions to "AI" below. We should think of AI's disruption as unfolding over time and having already begun. The process of adoption and adaptation will be ongoing and will have disparate and unpredictable consequences for workers in different occupations, industries, and regions. We cannot afford to wait until AI reaches some discrete milestone to adjust policies and interventions.

Disruption may well arrive at a faster pace than in previous periods of general-purpose technological advance and reach a larger scale than in prior advances. Indeed, new models are rapidly outperforming human benchmarks in an array of skills. But the future is far from certain, and some industry experts and firms continue to doubt that AI is having and will have a large disruptive effect, particularly on the labor market.[2] In light of this uncertainty, the private-sector and public-sector responses should both evolve and embrace risk management.

Taking this approach means identifying, monitoring, and proactively mitigating potential risks, including labor market displacement and shifts in and potential erosion of sources of current tax revenue. Responses should be flexible to allow different paths for model capabilities and business adoption to unfold. For businesses, such flexibility means developing programs that help workers gain skills to use AI effectively. For the public sector, this adaptation means reforming the tax code to be flexible to different types of economic activity. To be sure, many of the reforms we suggest below would be prudent to undertake even if AI results in much smaller economic shifts than many predict, making them sensible risk-management opportunities.

2. Maintaining connection to productive activity is an important part of a flourishing society.

Despite the possibility that advanced AI models might outperform humans at most or all tasks, we do not assume a future in which AI replaces all human work.[3] Indeed, as we describe, there

[2] For an illustration of these different views, see Carino 2025.

[3] Indeed, demand for some occupations could increase with AI adoption via the familiar "Jevons Paradox." Under this scenario, greater productivity from AI reduces the effective cost of an input—labor in this scenario—and thereby lowers the cost of the good or service, which ultimately results in greater demand for labor (see, for

are good reasons to believe that humans will continue to play a role in economic activity, and the private- and public-sector responses to these developments should prioritize active participation in the economy among working-age adults.

Participating in the economy means gaining economically valuable skills and having the opportunity to work at reasonable earnings. We should take as a goal that the economy should continue to offer widespread opportunities for individuals to gain skills and earn enough to support themselves and their families. Work not only generates earnings but is also a source of identity and purpose, and employment has been associated with higher overall well-being (Winkelmann and Winkelmann 1995). Economic disconnection also generates large costs—both personal and social. Technology-generated disconnections can have negative effects on children (Rege et al. 2011). They have also been provocatively connected with "deaths of despair" (Case and Deaton 2017). As a consequence, public policy has an important role in connecting people to the economy.

Business leaders have a role to play as well. Even the essential private goal of firms—to maximize long-term shareholder value—can (and, we argue, should) include acting as stewards of the community as a way of serving its long-term interest. As we describe, economic disruptions can breed low social trust and discontent, leading to policy responses that cut off the benefits of economic openness to further technological advances.

3. Building institutions—private and public—that can manage structural transition is crucial.

The opportunities and challenges this paper addresses come at a pressing time, when trust in the country's major institutions is historically low: In 2025, just 28 percent of Americans expressed "a great deal" or "quite a lot" of trust in major US institutions, down from 49 percent in 1979 (Brenan 2025). Structural changes from globalization and past technological advances have contributed to skepticism about the market economy's ability to deliver growth with widely shared benefits. Even today, the government's ability to address market failures or provide basic services is low by both historic and international standards (Liscow 2024).

Navigating this new transition will require improving existing institutions and designing new ones. We should leverage time-tested institutions where appropriate, such as by investing in America's community college system for skill development that matches employment to opportunity. Yet the inability to help dislocated workers remain connected to the economy amid prior episodes of automation and globalization, reflected in today's declining confidence in major institutions, should be a motivation to experiment with new approaches as well. Redesigned social insurance programs that support workers while they gain new skills are particularly necessary.

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instance, Aghion et al. 2025). Alternatively, as we describe later, other economists believe that for many forms, AI as currently developed will replace both tasks and jobs (see, e.g., Acemoglu 2025).

4. Distinguishing long-run outcomes from outcomes in a transition is crucial.

The core economic questions about AI regard this technology's overall effect on productivity, labor market outcomes such as wages and employment, and wealth. When considering these questions, economists often focus on the "steady state" outcomes over the long run. For example, in a different setting, economists have broadly agreed that freer trade benefits Americans through increased productive efficiency (see IGM 2012, for example). This assessment of the effect of trade reflects a focus on steady-state outcomes.

While such effects are, of course, important to evaluate, the transition to such a point can be painful, bringing disruption for current workers that creates political economy concerns. Such concerns are important because, if not addressed, they could put the potential economic gains from the development and adoption of new technologies at risk. When individuals do not believe they benefit from technological advances and economic openness, they may opt to slow such forces. In a democratic society, this reaction can take the form of electing political candidates who share skeptics' views and who then pass legislation or enact regulations that stymie openness that might generate overall economic growth.

This distinction holds whether the long run brings positive effects—following the path of previous general-purpose technologies, bringing greater wealth, wages, and employment[4]—or negative, such as in a scenario in which AI displaces most human labor. Moreover, the transition does not have to generate large aggregate effects to be salient politically.

An instructive example, discussed in detail by Strain (2024), is the political realignment resulting from the economic disruptions that followed China's entrance into the global trading system in the 1990s and first decade of the 2000s and subsequent dominance in manufacturing (the "China Shock"). First, job losses in the United States during the transition period were small relative to aggregate job churn over that time. Acemoglu et al. (2016) calculate that greater openness to trade from China led to 2.4 million fewer jobs in the decade between 1999 and 2011, or a loss of 240,000 jobs per year on average.[5] In that timespan, across the US economy, 4.2 million workers separated from their employer each year on average (US BLS 2026). Moreover, Autor et al. (2024) document that places negatively affected by the China Shock began to regain employment after 2010. Yet the economic shock during the transition generated a sharp political reaction against free trade: Congressional representatives in districts that suffered larger declines in employment due to the China trade shock shifted significantly toward support of protectionist trade policies (Feigenbaum and Hall 2015).

To maintain the economic openness that drives economic growth amid structural change, we need strategies to prepare and reconnect people to the economy. Otherwise, political economy

[4] For example, the productive gains created by Britain's First Industrial Revolution ultimately fostered real wage growth for the average British worker, but such gains took several decades to appear (Allen 2009).
[5] Importantly, such estimates focus on changes from employment due to import competition, but they do not account for expansions in employment due, for instance, to expansion of exports.

concerns will result in walls that seek to stop change—instead of bridges that prepare individuals for that change.

2. Actions by Workers and Firms in the Short Run and Long Run

As Robert Seamans's paper in this volume details, while research exploring adoption among specific firms finds that AI raises worker productivity, such gains do not yet appear to have affected aggregate productivity statistics or generated material labor market disruptions (chapter 1, this volume). Brynjolfsson et al. (2026) find signs that adoption of AI is slowing employment for entry-level workers: Beginning in 2022, young workers in AI-exposed occupations suffered a relatively larger decline in employment compared to older workers in similar fields and to similarly aged workers in less-exposed fields. But others find that employment for younger workers has been negatively affected by forces evolving at the same time, including the rise of remote work, because employers might be hesitant to hire less experienced workers on distributed teams (Emanuel et al. 2026). Looking at the labor market more broadly, unemployment has in fact been rising faster among those in the *least* AI-exposed occupations (Eckhardt and Goldschlag 2025).

Over the long term, the impact of AI on employment and wages largely hinges on two dynamics. First is whether this technology automates a job's tasks without creating new ones that rely on the worker's human expertise—the so-called labor-reinstating effect of automation described by Acemoglu and Restrepo (2019). Examples of such an effect abound in prior episodes of technological disruptions: In the 1980s, the adoption of computers in the financial industry automated many tasks previously performed by loan application analysts, but these tasks were replaced with new, more-specialized tasks requiring human expertise. This effect can also generate new occupations entirely, such as the advent of web developers amid the innovations in network technology in the 1990s (Lin 2011).

Second, the impact depends on whether a productivity-enhancing technology ultimately raises demand for a sector's output—the income elasticity, as laid out by Comin, Lashkari, and Mestieri (2021). In other words, as individuals' incomes rise because technology makes goods cheaper, does demand rise in line (high income elasticity), or do individuals spend a smaller share of their income on that good (low income elasticity)? Consider the contrasting examples of manufacturing and healthcare. The automation of textile manufacturing beginning in the 1950s dramatically improved productivity and lowered prices of produced goods. Employment fell because, as clothing became relatively less expensive, consumers spent a smaller share of income on those goods (Rowthorn and Ramaswamy 1999). By contrast, productivity gains in a sector such as healthcare might not result in employment declines because as healthcare prices decline, consumers will demand more healthcare services.

Applying such a framework to the current and medium-term projected capabilities of AI tools, four primary types of disruption emerge: First, AI will likely reduce demand for many jobs by

automating tasks in low-income-elasticity sectors, without a corresponding labor-reinstating effect. Second, the labor-reinstating effect will act to reshape many roles, changing the skills composition of existing occupations. Third, it will create bottleneck jobs. Fourth, it will create new work, new occupations that will emerge from new skill demands. Below we describe these different scenarios, with a view toward what each implies for worker and firm adaptation.

Scenario 1: AI automates enough tasks to reduce labor demand.

In this case, it is likely that AI tools can perform enough tasks within certain occupations to reduce labor demand. Such jobs may involve routine, programmable tasks (i.e., customer service representative), mirroring the effects of prior episodes of technological disruption.

But a defining feature of AI tools relative to such previous periods of technological advances is the capability to perform tasks across a range of occupations, including those involving nonroutine, cognitive tasks (Massenkoff and McCrory 2026). Such occupations, which have often required a college degree or greater, may see reduced demand because of AI's capabilities.

Scenario 2: AI reshapes work.

In certain occupations, AI technology may automate many tasks, but keeping humans in the loop will remain important. The key factor in determining how AI will affect wages and employment within these reshaped jobs is the type of tasks humans are left to perform. On the one hand, as Autor and Thompson (2025) lay out, when technologies eliminate higher-skill tasks (as inventory management systems did for warehouse workers), more people can enter this occupation, and employment expands but wages fall.

When, on the other hand, automation removes the simpler tasks (as accounting software did for bookkeeping clerks), the remaining work becomes more specialized, fewer workers are qualified to enter these jobs, and wages rise. In many cases, AI may automate the rote tasks within knowledge work, leaving those that require expertise, context, and judgment, such as evaluating output from AI tools or emphasizing the human-centered components of the occupation.

For example, while the task composition of software engineers involves work AI can replace, such as generating code, it also involves elements that require judgment and expertise (such as system design and translating business needs to technical solutions) (Emerson et al. 2026). In this way, AI tools may reshape a software engineer's work, moving it away from coding and toward system-level thinking.

Scenario 3: Economic value flows to "bottleneck jobs."

Relatedly, AI's capabilities to enhance productivity remain uneven across sectors and occupations within sectors. Despite gains in AI usage there are many tasks it cannot yet perform, and jobs with those tasks will receive economic value.

In the past, such jobs have included "bottleneck jobs," such as a truck driver moving harvested grain to factory or from factory to grocery store (Jones 2026). Productivity has improved dramatically within the harvesting and factory refinement components, where costs have fallen. But costs of such goods have not fallen entirely in line with those gains because of the human element in transportation.

AI might eventually automate enough tasks to eliminate many occupations as capabilities improve, but in many goods and services the human element itself is part of the output, what Imas (2026) calls the relational sector. As he notes, even in a scenario where humans' basic needs are met by AI tools, social aspects of goods and services (such as status and exclusivity) become more important. In such a world, the relational sector will be a larger source of jobs for humans.

Scenario 4: New work: AI will create demand for new expertise, or existing expertise in new contexts.

Following the pattern of prior general-purpose technology adoption, increases in AI use will create demand for new occupations entirely, as was the case in prior episodes of major technological change: Autor et al. (2022) find that 60 percent of employment in 2018 is found in job titles that did not exist in 1940. Indeed, demand for new expertise is already appearing. One example is forward-deployed AI engineers, software developers working at AI firms but embedded within businesses to build customized AI tools (Financial Times 2025). Another type of new work is in AI control, orchestrating the output of various AI tools within a business. BAND, for example, is a company that builds systems that facilitate the interactions of AI agents. For instance, an agent answering a question via email may need to conduct data analysis using internal sales tools; such control or "orchestrator" tools facilitate interactions by directing the email agent to the appropriate place for such information. They also ensure that agents possess the credentials to access information (Franzen 2026).

Some economists, including Daron Acemoglu, see a limited role for the labor-augmenting channel as AI use increases, both within existing occupations and through the creation of new work. They warn that AI is on the "wrong track," with development and adoption emphasizing automation over augmentation (Dizikes 2024). In a global survey of 6,000 business executives, Yoztov et al. (2026) find that, over the next three years, 59 percent of US executives predict that the adoption of AI will have a "small positive" or "large positive" impact on productivity, but 43 percent also expect AI to have a "small negative" or "large negative" impact on employment in their own firm.

But that path of raising productivity while reducing employment can be influenced by the choices that policymakers and business leaders make. As we noted above, political economy considerations will surface amid fast-moving structural change, which should push firms instead toward being good stewards of the current workforce and of the community in which they operate. Business leaders should invest in preparing workers for and reconnecting workers to the economy to build support for market economy amid structural technological change.

To begin, firms can prioritize incorporating AI in a way that complements professional work. Humlum and Vestergaard (2025) survey 25,000 workers in 7,000 firms across 11 occupations (including accountants, customer support specialists, financial advisors, office clerks, and software developers) about use of AI chatbots and link responses to administrative data on earnings and hours worked. While finding modest productivity gains from the use of such AI tools overall, they find that firm-led investments in AI generated 10–40 percent greater time savings for workers compared to workers in firms without such firm-led initiatives and that new tasks (the labor-reinstating effects) were 20–50 percent more pronounced in workplaces that incorporated AI use in existing processes.

Similarly, Wang et al. (2025) compare how humans and AI agents complete work across several occupations. They find that AI agents complete end-to-end projects less well than they complete discrete, programmable tasks because they can invent data and otherwise introduce errors. Thus, relying on AI agents for end-to-end task completion (designing and writing a quarterly report, for example) can reduce overall productivity by 18 percent, after accounting for error correction. However, incorporating AI into distinct steps in a workflow where it can complete tasks with limited guidance can reduce costs by 24 percent. This research highlights the need for firm-level strategies where AI can complement tasks within human work rather than replace whole occupations, otherwise erasing productivity gains.

As firms incorporate AI in this way, the tasks human workers will be relied on to perform will shift, and firms should make complementary investments in their workforce to ensure their skills and expertise keep up with these reshaped jobs. They can take as examples successful models of such retraining programs from the past. For example, amid advances in network computing in the first decade of the 2000s, AT&T began to shift its business model toward software-defined networks, allowing it to store and analyze network data for new lines of businesslike ad sales. Such a shift reduced need for roles like hardware technicians and retail workers, while raising demand in STEM roles like data analysis.

To avoid costs of competing with outside firms for STEM workers and to preserve valuable institutional knowledge, leaders developed a “Workforce 2020” program to reskill current workers in occupations predicted to decline with the skills needed for emerging jobs where the company faced a skills shortage (Kerr et al. 2020). The firm revised tuition-assistance programs to cover new educational programs and created in-house tools to train employees. AT&T also gave employees flexibility in deciding which roles to train into and provided career counseling to help workers navigate the transition into these roles. By 2016, the company announced it had met or exceeded its training goals, including increasing the internal sourcing of STEM jobs by 20 percent (Donovan and Benko 2016).

Such efforts to invest in developing current employees’ skills today are beginning to emerge. Many, however, focus on the effective use of internal AI tools within current roles, rather than reskilling employees into new AI-enabled roles. Walmart, for example, has announced a

partnership with OpenAI to develop a free certification program through its internal program, Walmart Academy (Morris 2025). Financial firms have unveiled internal AI tools trained on proprietary data (JPMorgan's LLM Suite, for instance), paired with a segment-by-segment approach to training, such as helping data scientists build financial models and advisors create personalized advice (Waldron and Buehler 2025). As more significant AI-driven shifts in firms' business models take shape, and as the resulting skills gap within their workforce emerges, firms should look to examples like AT&T as a path to investing in their own employees in a way that benefits the firm and the broader economy.

Furthermore, firms must also think ahead about redesigning career pipelines, particularly for jobs in knowledge work. The labor-reinstating tasks that AI is poised to create are centered not solely around subject matter expertise but on judgment, systems thinking, and context. The skills to complete those tasks are often gained through on-the-job experience. Without addressing these pipelines, firms leave themselves vulnerable to a future where there remains demand for human work but a shortage of workers with the necessary skills.

Given the risk that workers in whom firms have invested resources in upskilling will leave, firms may underinvest in worker training programs. But industry-level partnerships and public-private partnerships can reduce this challenge by lowering the costs any one firm faces. A recent example of an industry-level partnership is the Center for Energy and Workforce Development (CEWD), which is a consortium of utility companies intended to fill skills gaps that the industry is facing by designing curricula and standardizing credentials for firms to use when working with local educational institutions.

Such a consortium today could produce best practices for integrating AI tools in ways that are complementary to human work and could develop standardized curricula and credentials for firms to use when training workers to use these tools. For example, IT companies including Cisco, Intel, IBM, and Google formed the AI Workforce Consortium, aimed at identifying and closing AI-related skills gaps, including prompt engineering and AI security, through the collection of data and production of training materials (Cisco 2026).

Public-private partnerships can range from the local level, with business partnerships supporting effective models of workforce development at community colleges, to the national level, with federal funding support. By analogy, the Marshall Plan combined resources from the public sector and leadership from America's business leaders to reconnect postwar Europe to the market economy.

Of course, workers themselves also have a role to play in developing new skills and finding new opportunities amid this transition. They should identify and move toward bottleneck jobs and new work.

For example, Hyman et al. (2026) examines the outcomes of participants in worker training programs based on the measured AI exposure of their previous occupation. He finds that workers

in high-exposure occupations experienced large wage gains primarily by transitioning into less exposed occupations—common examples of such a transition are customer service representatives retraining to become Nursing Assistants or Heavy Truck Drivers. On a smaller scale, he also finds evidence of success (measured by earnings gains) in programs building AI-complementary skills—Office Clerks moving into more general Administrative Support, for example. Over the long term, individuals could focus incremental education and training on specific preparation for bottleneck jobs and more broadly on gaining flexibility, intuition, and entrepreneurial vision to create employment value.

3. Public Policies During the Transition: Modernizing Social Insurance as Part of a "Mass Participation" Agenda

While firms and workers can play a role in ensuring a smooth transition path, AI advances can pose labor market risks too large for individual parties to bear in rapid-change scenarios. A set of policies deals with such risks today—including job loss during an economic downturn or wage loss caused by a disability. The labor market uncertainty brought about by AI calls for a social insurance program designed to both mitigate income loss and reconnect workers to productive economic activity during long-term structural change.

Some key labor market social insurance programs are designed to address cyclical disruptions. For example, unemployment insurance is designed to temporarily replace the income of workers who lose their jobs during a recession until employment opportunities reappear. The US experience assisting workers to adapt to structural changes in the economy is more limited and has not demonstrated evidence of large-scale success.

An instructive example is the effort to help workers adapt to trade-induced economic disruptions. Congress enacted the Trade Adjustment Assistance (TAA) program as part of the Trade Expansion Act of 1962. The program covered costs for retraining programs, provided income support (in the form of expanded unemployment insurance) conditional on enrollment in training programs, and offered relocation subsidies to workers who lost their jobs due to foreign competition. The evidence of the effectiveness of TAA is sparse, and positive effects from training often disappear after a time (Hyman 2018).

One smaller policy lever within TAA generated more unambiguously positive results: wage insurance. Older workers within the TAA program (aged 50 or older) were eligible for the Reemployment Trade Adjustment Assistance Program (RTAA), which did not require job training and paid half the difference between workers' pre- and post-separation wages for up to two years. Such a program has two features: The subsidy is conditional upon reemployment, and the size of the financial support is proportional to the magnitude of wage loss (that is, workers experiencing a larger decline in wages after reemployment see a larger wage insurance subsidy). Eligibility for wage insurance shortened unemployment spells and generated persistently higher earnings than those of just-ineligible individuals (Hyman et al. 2026). Importantly, this program

did not lead to older workers accepting lower-paying work. In fact, avoiding the scarring effect of long-term unemployment through speedier reemployment drove an increase in earnings.

Despite generally positive results, TAA was far too targeted to have a large impact and never gained political traction (as an example, case examiners had subpoena powers to investigate a firm's books to determine if workers had lost jobs due to foreign trade competition). In 2022, funding for the program lapsed, and TAA stopped certifying new participants (US Department of Labor 2022).

Looking beyond workers directly affected by trade, the country's broader public workforce-development system is largely governed by the Workforce Innovation and Opportunity Act (WIOA), formerly the Workforce Innovation Act (WIA). This initiative, in part, provides resources to help workers who have lost their jobs ("dislocated workers") reenter work through subsidized occupational training programs and job search assistance services. Eligible individuals receive a voucher that allows them to take part in training services through Eligible Training Providers (ETPs) certified through local or state workforce development systems, which can include community colleges, other nonprofit providers, and for-profit providers. The law requires that states develop regularly updated workforce development strategies and that programs run by ETPs lead to "in-demand" jobs, but states have wide discretion to determine the list of ETPs. Beyond funding training for individuals through vouchers, WIOA also provides a smaller set of funding for local workforce boards to support specific training programs (such as apprenticeship programs or sectoral employment programs, explained below).

Unfortunately, historical outcomes for dislocated workers participating in WIOA and its predecessor WIA are mixed and largely dependent on the type of training workers take part in (CEA 2016). Comparing outcomes from dislocated workers taking part in WIA training programs across 12 states from 2003 to 2005 to observationally similar workers who did not enroll, Heinrich et al. (2013) find that the program has no effect on employment or earnings. Using a different methodology, Andersson et al. (2024) similarly find no effect of participation in training programs on employment or earnings for dislocated workers. Positive effects have been seen in specific types of programs, particularly sectoral training programs, that feature strong employer involvement in curriculum development and intensive wraparound services for participants (Katz et al. 2022).

Researchers have highlighted several reasons for the broadly disappointing track record of public efforts to retrain dislocated workers. First, the United States spends a relatively small sum of funds on workforce development efforts compared to other developed countries. Looking at all spending on the labor market (including workforce development and unemployment insurance), the United States spent 0.02 percent of GDP in 2023, compared to the OECD average of 0.11 percent (OECD n.d.). As Orrell et al. (2023) put it, the United States may be stuck in a "low resource, low-efficacy equilibrium."

There are additional challenges with the way current funds are spent. First, Leigh et al. (2026) argue that the lists of training providers that states deem eligible for WIOA funds are often not aligned with states' own workforce development strategies (including projections of in-demand occupations). Second, the structure of WIOA is intended to foster a consumer-choice dynamic, in which funds flow to effective providers, but that dynamic is stymied by the patchwork of providers and poor information offered to participants about both occupational opportunities and provider training quality (Deming et al. 2023).

Furthermore, WIOA is only a small part of the country's broader workforce development system, aimed at helping workers in declining industries gain skills for employment in new occupations. For example, in 2024 about 182,000 individuals used WIOA vouchers for training (and just 87,000 of those were dislocated workers), while 5.9 million students were enrolled in community colleges (US Department of Labor n.d.; NSCRC 2026). Similarly, for Year Up, a sectoral training program that Katz et al. (2022) find effective at raising employment and earnings outcomes, only 2 percent of revenue comes from government funding (Deming et al. 2023). What is broken about current policy is the ability to connect workers to these programs. Despite efforts to improve information availability, websites like TrainingProviderResults.gov still lack consistent information on outcomes across programs, leaving participants to navigate a web of roughly 75,000 ETPs without clear and accessible information.

The historical record for assisting workers experiencing disruption shows that our tools are not prepared for the scope and speed at which AI may reshape the labor market. The country needs a new policy agenda to reconnect dislocated workers to an economy undergoing long-term structural change. That agenda should build on the success of prior programs.

Wage insurance. One example is reintroducing an expanded wage-insurance program for older workers. As with TAA, this program would replace a portion of older workers' wages for a period. But such a program should have reach beyond trade-affected workers. Older workers generally experience greater labor market scarring from other forms of disruption, including technological changes, and they recover less quickly than younger workers—in part because the returns to worker training programs are smaller for older workers (Johnson and Butrica 2012; Card et al. 2018). As laid out in Davidson and Slaughter (2026), because evidence suggests that AI substitutes well for high-skill (and high-wage) jobs, wage insurance is particularly well suited to facilitating reconnection to meaningful participation in the economy and insuring against wage loss for older workers during the AI disruption.

Personal Reemployment Accounts. For younger workers, who may see greater returns from retraining, we should reimagine the social insurance system to provide broader access both to temporary income support and to assistance gaining new skills.

Personal Reemployment Accounts (PRAs), which provide flexible funds for workers to use on training services along with a reemployment bonus, will allow for individual choice while incentivizing reemployment. This account can contain a set amount or can be linked to their

unemployment insurance account. Individuals could, for example, receive access to funds calculated as some multiple of their weekly benefit allowance and choose to use funds on eligible expenses—including training programs, intensive career counseling (which, as noted below, has been found to raise program completion rates), transportation, or childcare. They would then receive a payment upon reemployment within a certain amount of time of filing for benefits and lasting a minimum amount of time (say, six months of employment). As an example, a mid-career accountant laid off could use a PRA to purchase training through a community college or other credentialed provider to obtain a new certificate.

Recent evidence finds that reemployment bonuses structured as a fixed multiple of the weekly benefit are a cost-effective lever to reduce unemployment and raise labor force participation (Hobbs and Strain 2026). Furthermore, this structure, compared to one where the recipient receives all or a portion of the balance of the PRA as a bonus, avoids a tradeoff where PRA recipients reduce purchases of training services in hopes of receiving a higher bonus (O'Leary and Eberts 2004).

Importantly, such efforts to allow individual flexibility within a reimagined social insurance program must be paired with reforms to the current workforce-development system. Most importantly, state workforce development boards should regularly update the list of providers eligible to receive federal funding to remove programs that do not have a history of positive participant outcomes. Job centers must also do a better job allowing participants to enter the system to access up-to-date data on program outcomes. Unemployed workers are much more likely to participate in reskilling programs that involve a move into a new occupation when presented with data indicating that these programs will translate into employment opportunities (Delfino et al. 2026).

Second, the contours of AI-driven disruption—that is, the tasks required within *reshaped* jobs and *new* work that AI adoption creates—call for even closer ties between workforce development programs and employers. Reshaped jobs will increasingly rely on judgment and systems thinking, which are traditionally fostered by on-the-job experience. As Orrell (2026) puts it, "workforce development is being asked to solve one of the defining problems of the next decade: how to grow judgment when the experiences that produce it are increasingly pressured by automation."

Public subsidies for customized job-training programs have recently been found to help facilitate on-the-job experience. Federal and state grants to firms to design and implement training programs can raise firm-specific and transferable skills that lead to large wage gains for workers (Dillon et al. 2025; Millar 2025). Importantly in the context of AI's disruptions, Dillon et al. (2025) finds that most training programs aimed to increase workers' professional skills, such as leadership and process management—two skills likely to be in greater demand as AI reshapes occupations—and that firms offering these programs grow rapidly and raise wages.

Expanding resources for firms to conduct customized job-training programs is an evidence-based path for employer-led training efforts, keeping workers connected to the labor market as they gain new, economically valuable skills. Yet, there is still much to learn about which on-the-job training programs are most effective, and the nation's workforce development system should play a role in funding programs that build that evidence. Fortunately, those efforts appear underway: The Department of Commerce's Economic Development Agency recently announced a new AI Upskill Accelerator Pilot Program that aims to find new ways to help workers develop AI skills, primarily through sectoral partnership programs (EDA 2026). It funds programs through training providers and employers that design and deliver training programs, with an emphasis on developing models that fit different areas and industries and on monitoring outcomes like completions and employment placements.

Finally, as we outlined above, today's policies to reconnect displaced workers are a small part of the country's broader workforce development efforts. Policymakers should emphasize proven avenues of worker training and steer dislocated workers toward such programs. As a start, workforce development boards should also allocate available funding directly to other programs that have rigorous evidence of success.

Congress should also increase resources to community colleges through block grants. Community colleges play a large role in ensuring workers have skills throughout their careers—including in preparing and connecting workers to new careers through short-term (less than two-year) vocational training programs. First, as Hyman et al. (2026) documents, community colleges are beginning to create AI-related training programs (measured through program descriptions that include "Artificial Intelligence," "Natural Language Processing," and "Machine Learning"). This funding can help community colleges continue to update curricula. Second, as multi-employer groups develop standardized curricula that a community college can use to train students, the funds will provide resources to scale such programs—to return to the example of CEWD above, this multi-employer group partnered consistently with community colleges on curriculum design for careers with utility companies, an example that can be adopted to today's environment and expanded with additional funding (Economist Intelligence Unit 2014). Finally, and perhaps most importantly, funding will allow community colleges to expand wraparound services—such as career counseling, which is often expensive but critical to program completion (Evans et al. 2020).

As the coming wave of disruption spreads unevenly, it is likely to affect different groups differently—by educational attainment, age and experience, occupation, and industry. As those groups are concentrated geographically, this shock will likely also affect communities to different degrees. Given the uncertainty over the contours of labor market disruption that will occur, it is correspondingly uncertain how such geographic shocks may unfold. For instance, it is possible to imagine AI reducing demand for highly educated white-collar work, leading to a negative employment shock to major urban superstar cities; alternatively, this technology may automate work primarily found in smaller, low-cost cities (see, for instance, Putzier 2026). Given

now-recognized frictions involved in people moving to areas of new economic opportunities, policymakers should also direct support to communities. Such support can be provided, for example, by scaling community-college assistance to specific measures of local economic distress—increasing as the unemployment rate increases or the employment-to-population ratio in an area falls—as recommended by Bartik (2020).

4. Tax Policy in the AI Economy

Two longer-run challenges for tax policy emerge from the advance of AI. First, the shift in how output is produced may move resources away from those providing significant sources of federal tax revenue. In 2022, individual income taxes provided 54 percent of all federal revenue, and wages and salaries made up 64 percent of all adjusted gross income on individual tax returns (CBO 2026; Parisi 2024). While AI-driven productivity gains may raise national income, such gains may largely accrue to capital, which is taxed at a rate lower than labor income is. Disruptions that reduce labor's share of income will work to exacerbate both deficits and concerns over high profits in technology firms.

Such a decline in the labor share would continue, if not accelerate, current trends. In the United States, labor's share of income remained around 63 percent in the second half of the twentieth century. Early in the first decade of the 2000s, the labor share of income began a sustained decline that researchers have attributed in part to prior episodes of automation, the rise of "superstar firms," market concentration, and changes in individual income and corporate taxes (Karabarbounis and Neiman 2014; Autor et al. 2020; de Loecker et al. 2020; Smith et al. 2022). It now stands at 54 percent, its lowest level going back to 1945 (Audoly et al. 2026).

Second, the labor market response described above will likely demand greater public investments. But our capacity to respond will be limited by already-strained public finances. The US budget deficit averaged 2.8 percent of GDP from 2010 to 2019, and the Congressional Budget Office projects that it will more than double to an average of 6.1 percent over the next ten years (CBO 2026). As a result, the CBO projects that the federal debt held by the public, which reached 100 percent of GDP in March 2026, will reach 120 percent in 2036 and 176 percent by 2056. Even under optimistic scenarios in which AI raises productivity growth between 0.5 and 1 percentage point per year over the next 30 years, federal debt is projected to continue to rise to between 126 and 136 percent of GDP by 2055, without factoring in the additional public resources needed to support displaced workers (Dynan et al. 2026).

These forces require that an appropriate policy response to AI include reform of the federal tax system that provides adequate resources while encouraging investment and growth. Today, the United States taxes labor and capital income for both revenue and redistribution, trading off equity gains from redistribution (i.e., progressive taxation) with efficiency costs of taxation (i.e., distorting labor supply, savings, and investment decisions).

Korinek and Lockwood (2026) find that under a scenario in which AI reduces labor's share of income, a consumption tax is optimal. Importantly, they show that a broad-based tax on consumption can achieve the same government revenue and allocation of resources as a tax on a household's labor income and initial capital. Thus, households are indifferent between facing taxes on initial capital and labor income (and using post-tax funds on consumption) or being taxed at the point of consumption. The authors conclude that, as labor income erodes and capital income drives consumption, the government should then shift toward taxing consumption.

Such a tax reform has, of course, been long suggested by economists. Relative to the current income tax, a broad-based consumption tax would raise saving and investment, leading to higher productivity and incomes. While the term "consumption tax" can call to mind a European credit-invoice value-added tax, the United States could implement the tax change in a simpler fashion more easily tied to accounts currently maintained for taxation. Namely, a consumption tax at a given rate is arithmetically identical to a combination of a wage tax and a business cash flow tax at the same rate.

A cash flow tax taxes a firm's revenue, minus all its expenses including investment. That is, it would allow businesses to expense investment immediately, boosting investment. It would also disallow nonfinancial companies from making interest deductions, because in contrast to an income tax, a cash flow tax treats debt and equity the same. This shift removes an important tax incentive for firms to allow themselves to be leveraged. A cash flow tax is also much simpler than a corporate income tax, which requires complex depreciation schedules.

Cash flow taxation shifts the tax burden toward high profits, useful in an environment of increased profit concentration in highly profitable firms. This benefit arises because the cash flow tax removes taxes on what economists call "normal return' on investment, or the cost of capital. Companies would instead pay only on profits above this amount.

Because the cash flow tax offers fewer distortions of saving and investment than the income tax, it is a more efficient instrument for raising incremental revenue on a fiscal consolidation. While the bulk of fiscal adjustment requires adjustment in federal spending, higher revenue would almost surely be part of a politically agreed-upon package.

To maintain progressivity, this consumption-based tax could be implemented along the lines of the "X tax" proposed by Bradford (1986). A business cash flow tax that exempts input costs (including wages and materials) and the cost of capital investments could be paired with a progressive wage tax. This structure has the desirable property that taxes would fall on profits generated by returns on capital above the riskless rate—including those earning rents from AI (Gentry and Hubbard 1997).

Power and Frerick (2016) estimate the fraction of corporate income attributable to risk-free and excess returns from 1992 to 2013. They find that the portion attributable to the risk-free return has fallen from an average of 40 percent in 1992–2002 to 25 percent in 2003–2013. Their

measure of excess returns is highest in the information and software/technology sector, suggesting that much of the rise in income within these sectors amid the adoption of AI will be captured by this tax. This shift in relative taxation rebalances the tax system and can raise funds to the structural adjustments we described earlier.

The second desirable feature—assuming the ongoing importance of labor income—is that the tax system would retain the progressive structure of the current personal income tax system. This proposal pairs the corporate cash-flow tax with a progressive wage tax, featuring a wage subsidy at the bottom that would generate the same pro-work incentives as today's Earned Income Tax Credit (Schanzenbach and Strain 2020).

Moving toward such a system is possible within the current structure of the US tax code. Both the Tax Cuts and Jobs Act of 2017 (TCJA) and the One Big Beautiful Bill Act of 2025 (OBBBA) took steps to move the US corporate tax code from its current structure as a tax on corporate income (taxing revenue minus costs of production, allowing for a deduction of investment costs over time) toward a cash flow tax (a tax on cash received minus cash spent on business activities, including materials, wages, and any investment costs). The two forms differ primarily through whether to allow businesses to immediately deduct investment and research and development (R&D) expenses ("full expensing," as a cash flow tax would), or to deduct the costs over time as the investment depreciates, as an income tax would. The TCJA allowed for full expensing on a temporary basis, and then the OBBBA allowed for full expensing only of machinery and equipment permanently and expensing of R&D.

This hybrid structure, however, distorts incentives in a way a pure income tax or cash flow tax would not. It favors some forms of investment (in machinery, for instance) over others (say, structures), and the current expensing rules are layered on top of deductions for interest expenses on debt, distorting firms' decisions of how to finance investments (see Furman 2020 and Gale et al. 2026).

Congress can move toward a pure cash-flow structure by completing the shift to full expensing (allowing immediate expensing of all investment costs) and removing the deduction for interest payments. Pairing this change with a border adjustment—removing the corporate tax on revenue from exports and adding that tax on revenue from imports—would put domestic producers on a level playing field with foreign producers and would turn the tax from one on domestic production to a tax on domestic consumption, as Korinek and Lockwood (2026) describe.

With an eye toward increases in inequality during rapid technological advances, Congress should also reform the estate tax. Currently, heirs inherit assets on a "stepped-up" basis—the assets they acquire are revalued to current market value at inheritance, and the tax on gains upon sale is calculated using this stepped-up value as the cost basis. This method effectively wipes away a significant portion of capital gains that go untaxed. Replacing the stepped-up basis with a carryover basis—in which the gains are calculated at the original purchase price of the asset and taxing gains upon sale rather than at death—would improve fairness and raise additional

revenue: The CBO (2024) estimates that this change would raise $197 billion over the next ten years.

Policymakers could examine other, often equivalent, options to ensure that households share broadly in the economic gains from technological advances. One option mentioned in policy discussions is the distribution of equity shares across households—for example, through a sovereign wealth fund, distributing a regular dividend from fund returns. This mechanism is equivalent to directing a portion of the corporate tax toward households but would make the tie between AI firms' gains and households' benefits more directly apparent. Such ideas, though, raise incentive and complexity concerns relative to the reforms of taxation and social insurance that we outline. Of particular importance is the question of whether the government would directly own shares of firms, as currently proposed (see, for instance, Shapero 2026 and Broughel 2026). Such an arrangement raises concerns about the proper role of the government in the market economy, including the prospect that public officials might aim to advance social or political goals through these ownership stakes rather than maximize financial return (see Dynan et al. 2026).

Tax and social insurance reform offer a better response to medium-run and long-run labor market shifts from AI than the creation of a Universal Basic Income (UBI) that provides untargeted income support to all Americans. As Kearney and Mogstad (2019) observe, not only is UBI regressive in comparison to the current tax-and-transfer system, but it would do little to promote opportunity and connection to economic activity for those affected by technological advances. Many studies looking at transfers of comparable sizes to a UBI find large and persistent declines in labor supply among beneficiaries (see, for instance, Cesarini et al. 2017; Maestas et al. 2013). Investment in human capital development, paired with temporary income support, is a proven path to advance economic opportunity and participation.

Furthermore, taxes that apply to certain activities, particularly those targeted to AI, warrant caution. Unless such taxes clearly address a negative externality or market failure, those taxes (such as a compute tax on developing a new model or tokens consumed while using AI) will restrict productivity-enhancing investments. Policymakers should think about how to apportion a larger pie (through policies above), but such taxes will largely act to shrink the size of the pie.

5. The Importance of Processes In Addition to Policies

AI's structural change is arriving at a time when state capacity is relatively low. There are many examples during COVID of the limits of public capacity, particularly within the labor market, including coordinating the unemployment insurance system. That period also showed the potential for effective economic and health responses in a crisis (setting up a new business continuity program in the Paycheck Protection Program and distributing vaccines on a condensed timeline).

We should employ the same urgency in the conversation about a coordinate response to AI, if only from a risk management perspective. One lesson is that processes matter. COVID involved interagency coordination. AI responses wll involve the Departments of Labor, Education, and Treasury. Interagency processes can coordinate policy response in a way that cuts across agencies. A current example is the National Permitting Council, aimed at coordinating the multi-agency permitting process for significant infrastructure projects (Permitting Council 2024). As with the National Permitting Council, an AI Economic Engagement Task Force should have clear goals and facilitate appropriate public and private responses.

Given the uncertainty around the economic impact, such a task force could also coordinate US statistical agencies' efforts to collect and disseminate data. The task force could include members of US statistical agencies, including the Census Bureau, Bureau of Labor Statistics, and Bureau of Economic Analysis, to guide the coordination of public and private data and facilitate new data collection, as proposed by Goldschlag (2026).

Historically, we can look for an example in efforts to smoothly transition the post–World War II economy to peacetime levels of activity. In the early 1940s, business leaders were able to predict that the looming decrease in demand after war efforts ended, coupled with the return of GIs after the war, would likely lead to stagnation and unemployment if left unaddressed. Executives of leading companies, including Studebaker and Eastman Kodak, formed the Committee for Economic Development (CED), devoted to developing and enacting solutions to the country's economic challenges (McCabe 1949). Proposals from the CED focused on promoting maximum employment and price stability shaped the Employment Act of 1946, and the committee's program of European economic cooperation formed the blueprint for the Marshall Plan to rebuild the European economies after the war (Conference Board n.d.).

To implement the Marshall Plan, Congress established the Economic Cooperation Administration, sitting within the Department of Commerce and led by Studebaker President and CED Chairman Paul Hoffman. Beyond direct financial assistance, the plan also enlisted the help of US business executives to provide technical assistance to train European business leaders in productivity-enhancing methods of production and management (CRS 2018). This model of relying on business leaders to execute on broad outlines set by government is one that policymakers could follow in developing strategies to navigate a new period of economic transition.

Conclusion

While the ultimate effects of AI on income and employment are highly uncertain, risk management principles justify steps today to ensure that those steady-state gains are widely shared and that the transition period prioritizes maintaining mass participation in the economy. Inattention to managing the transition risks the loss of societal support for technological progress that can deliver economic gains. For the private sector, these steps involve business leaders

recognizing their long-term interest in serving as stewards of their communities, investing in AI in ways that are complementary to human skills and rethinking career pipelines today, while individuals take steps to identify and prepare for new opportunities. In the public sector, policymakers should develop a new social insurance program to address the risks that are too large for individuals to bear. This program would pair short-term income support with evidence-based paths to gaining valuable skills. Tax policies must also adjust to a further decline in labor's share of income and rise in wealth concentration in order to ensure—in an already-strained budget picture that the public has resources to promote widespread prosperity.

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