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Chapter 7

An Economic Framework for Understanding Artificial Intelligence

Artificial intelligence (AI) systems touch the lives of virtually every American. They range from simple systems like text autocorrect to complex algorithms capable of setting prices, driving cars, and writing essays. In recent years, AI systems have advanced rapidly as recent developments in computing, data availability, and machine learning models have simultaneously come together to produce rapid improvements. Still, much remains unknown. Agrawal, Gans, and Goldfarb (2022) suggest that AI is in "the between times," where society has begun to see the technology's potential but has not come close to fully realizing it. While AI's capabilities will depend in part on the technology itself, its effects will be shaped by economic, regulatory, and social pressures. How society deploys this technology and what technology-specific guardrails are implemented will be critical factors in determining both the breadth and magnitude of its effects.

Economic incentives play a central role in how decisions are made. An economic framework, combined with a basic understanding of AI technology, allows us to make predictions about when, how, and why AI may be adopted. While such a framework can also tell us what broader effects AI adoption may have, applying economic insights to an evolving and proliferating technology like AI is especially challenging. However, it is also especially valuable, because decisions made at the onset of a new technology have a greater influence on its eventual impact. This chapter begins with a basic discussion of the technology and then examines how the inputs to AI have changed, with a particular focus on the concept of diminishing returns and the key role of data in AI systems. Next, it examines the economic incentives for AI development and adoption, including on macroeconomic outcomes like productivity. The chapter's third section adapts standard economic models to explore AI's potential effects on labor markets across the earnings distribution, demographic groups, industries, and geographic areas, updating previous work with new data and augmenting it with a novel analysis based on not only exposure to AI but also the complexity of each task. Finally, the fourth section examines important economic issues for upcoming policy choices related to the law and regulations, competition issues, and social outcomes (e.g., how technology interacts with existing inequalities like racial discrimination).

Toward "Intelligent" Automation

Since Adam Smith's first observations about how machinery allowed for the division of labor, economists have studied the economic effects of technology (Smith 1776). Many technologies—like Smith's example of specialization by workers in a pin factory—enable more output from the same inputs. Some technologies, however, enable an increase in capital to reduce labor. Economists call this class of technologies automation (Brozen 1957; Zeira 1998; Acemoglu and Restrepo 2018).[1] This definition of automation is broader than factory machines and computers, and includes technologies that have been in place for centuries. For example, according to this definition, a windmill set up to grind wheat would be a kind of automation. These kinds of technologies can have broad effects—including on prices, wages, input usage, and output—which in turn may resonate throughout the economy.[2] As discussed later in the chapter, a wide range of potential uses of AI entail this kind of capital-for-labor substitution, making it an automation technology.

To understand the incentives for AI's development and adoption, it is necessary to have a basic common understanding of the technology. The field of AI is broad and changing quickly. What follows is a stylized representation of basic concepts that may not be applicable to every circumstance.

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[1] In some cases, automation technologies simply replace existing labor. In most cases, however, automation technologies allow for greater output than before, and in some cases, they may allow for the creation of products that would never be economically viable to create by hand.

[2] While this definition's emphasis on the word "substitution" might suggest that automation technologies invariably reduce employment, this need not be the case. Because automation technologies make certain production steps faster and cheaper, they can increase overall demand for both the product being made and related products. Additionally, labor is generally required to create and maintain such technologies.

Although definitions of AI vary across fields and purposes, AI systems are generally understood to take in data and,[3] through statistical or computational techniques, make predictions.[4] Some have called them "prediction machines" (Agrawal, Gans, and Goldfarb 2018). In many cases, predictions are used to inform recommendations or determine how other components of the system will act. For example, AI systems have been developed to solve challenging scientific problems, and they are widely used to set prices and rank job candidates. In other cases, as with some generative AI models, these predictions themselves are simply aggregated to form an output.[5] In this context, predictions are far broader than forecasting the future, and can indeed be about practically anything for which reliable data can be obtained.

The ability to make predictions often allows improved decision-making, even in the face of uncertainty. As a result, AI systems can automate more tasks than prior technologies and improve the work quality of existing processes. For example, stamping machines automate the creation of certain kinds of metal parts, but automated systems may have struggled to handle situations where the production process had inherent variation, like harvesting produce. Today, an AI-augmented system might use sensor data to predict when fruit is ripe and how to detach it, allowing that production process to be further automated (Zhou et al. 2022). Likewise, autocorrect systems are an example of how AI increases the quality of work. Originally, these systems relied on lists of often-mistyped words and their correct spelling. When the software detected misspellings, it suggested a correction. Advanced autocorrect systems using AI employ dictionaries, information about what all users tend to type, and data from individual users' past typing activities to predict what they intend to type (Lewis-Kraus 2014). As a result, the systems detect not only misspellings but also incorrect words.

Figure 7-1 portrays a stylized diagram of how AI systems interact with traditional automation in order to emphasize key ideas relevant to the economic discussion.[6] During training, an algorithm is applied to data

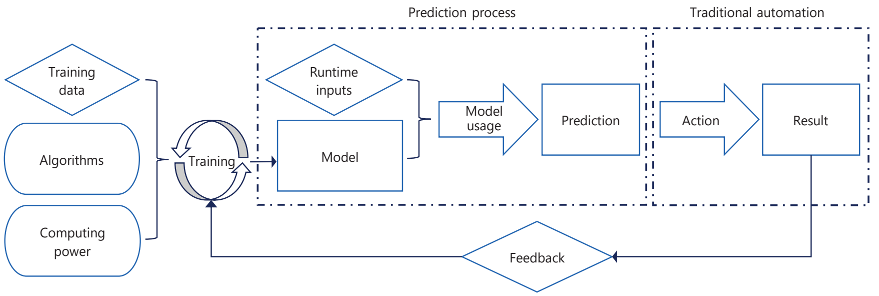
[3] In this context, data can refer to any machine-readable information and is not limited to the kinds of datasets that economists might be most familiar with. It can potentially include digitally encoded text, images, sound, video, information on real-time human input, simulation feedback, and many other categories of information.

[4] For example, Executive Order 14110 (2023) defines AI systems as those that "use machine- and human-based inputs to perceive real and virtual environments; abstract such perceptions into models through analysis in an automated manner; and use model inference to formulate options for information or action." It defines an AI model as something that "implements AI technology and uses computational, statistical, or machine-learning techniques to produce outputs from a given set of inputs."

[5] Executive Order 14110 (2023) defines generative AI as "the class of AI models that emulate the structure and characteristics of input data in order to generate derived synthetic content. This can include images, videos, audio, text, and other digital content."

[6] Of particular note, figure 7-1 emphasizes the role of data in AI, though in many cases it might be more accurate to more generally refer to inputs.

Figure 7-1. A Stylized Diagram of How AI Extends Automation with Prediction



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using computing power.[7] In some instances, this training process can be quite complex and involve many iterations; often, it includes validation and testing steps, which are not shown in the figure. The training process produces a model, which is combined with data at the time it is used to create a prediction. Such predictions, however, are rarely useful until they are applied in some way. In typical AI systems, one or more predictions are used to take actions automatically. For example, a large language model might make many predictions about individual words based upon a user's request, and then the system aggregates them into one output to display. The same kind of model in a different context, such as customer service, might not only respond to the user but also issue a refund. Finally, the results may be evaluated to create feedback to help further refine the model in the future, and some systems learn continuously to further improve performance and prevent degradation.

As figure 7-1 illustrates, AI systems can integrate multiple sources of data, often at different points and for different purposes. For example, in the diagram, data may enter the system at the training, runtime, and feedback stages. In some cases, human input can be an important part of development as well (Amershi et al. 2014; Mosqueira-Rey et al. 2022; Ouyang et al. 2022).[8] AI's reliance on data raises unique economic issues, including ones related to competition and transparency. These issues are discussed in more detail later in the chapter.

Figure 7-1 also illustrates that having the requisite algorithm, data, and computational power to make predictions is a necessary but not sufficient condition for AI-based automation. For example, even after a model

[7] Some types of AI systems—for example, systems that rely on coded rules rather than machine learning—may not make use of training data (e.g., Taddy 2019).

[8] In some cases, a large amount of human input has been important in fine-tuning models to ensure acceptable performance, and serious concerns have been raised about the pay and working conditions of those workers (Perrigo 2023; Bartholomew 2023).

is developed for self-driving cars, it may not be deployed in older cars that lack the sophisticated sensors necessary to collect the requisite data while being driven. Similarly, practical limitations on actions may limit the scope of AI deployment. For example, many tasks involving flexible materials have proven very difficult for robots to handle (Billard and Kragic 2019). AI systems may ameliorate these problems, but such physical limitations may continue to prevent the automation of tasks even where the system has sufficient predictive power. Finally, in some cases, translating prediction into action may require making decisions that we are unwilling or unable to fully delegate to AI due to ethical or other concerns (Agrawal, Gans, and Goldfarb 2018).

Prediction Is Improving but Faces Constraints

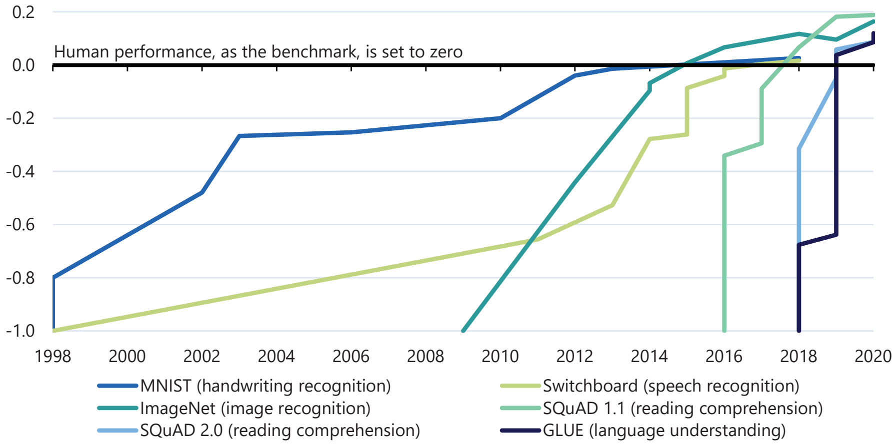
In general, prediction quality can be thought of as the output of an economic production function. Developers choose an option from a variety of different algorithms, each of which can be optimized subject to the developer's constraints, such as development time, data availability, or budget for computational resources. Economists represent these kinds of situations where agents are maximizing an objective subject to restrictions as constrained optimization problems (Mas-Colell, Whinston, and Green 1995). Typically, in a constrained optimization setting, not all constraints are equally binding, and some may not be binding at all. As an extreme example, a complete lack of data on a problem could render a lack of computational resources irrelevant. Of course, these constraints are constantly changing as new data become available, as computational resources become cheaper, and as research develops more efficient algorithms and other innovations.[9] The relationship between design and development choices (e.g., algorithms, data, and computational resources) and prediction quality is thus complex and varies from situation to situation. In part because of the complex interactions of these constraints, predictions about AI's future capabilities have often been wrong (Armstrong, Sotala, and Ó hÉigeartaigh 2014).

It is potentially more informative to look at how AI performs various tasks. Figure 7-2 shows the performance of the best available AI model in each year on a number of benchmarks, rescaled to compare with human performance on the same test. Comparing AI's performance with human performance in this way is potentially useful for understanding if and when AI systems may be deployed as a substitute for labor, although researchers have raised serious concerns about these kinds of benchmarks, both in the way they aggregate performance (e.g., Burnell et al. 2023) and in the way

[9] Research can also alter these constraints in other ways. For example, a great deal of work in both machine learning and econometrics is done to find ways to compensate for data limitations, often at the cost of increased computational requirements.

Figure 7-2. AI Capabilities Over Time and Across Tasks

Test scores of AI relative to human performance



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Sources: Adapted from Hutson (2022), based on Kiela et al. (2021); CEA calculations.
Note: MNIST = Modified National Institute of Standards and Technology; SQuAD = Stanford Question Answering Dataset; GLUE = General Language Understanding Evaluation. Benchmark performance is scaled so that –1 is initial performance and 0 is human performance.
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selected metrics may create the fictious appearance of sudden large performance improvements (Schaeffer, Miranda, and Koyejo 2023).

Figure 7-2 shows that AI systems have approached human performance at very different rates across the various benchmarks. In some cases, the progress of AI was significantly influenced by data availability (e.g., Xiong et al. 2016; Sharifani and Amini 2023). Because of the way in which they naturally produce and share digital information, the Internet and smartphones have been important data sources. Similarly, small, cheap sensors have dramatically changed data availability in industrial and maintenance operations. These complementary technologies have been especially important in creating the volume of data necessary to train modern AI systems, and especially foundation models.

In most economic optimization problems, the marginal value of an input (data, computational resources, etc.) tends to decrease as more of it is used, as measured by the amount of output in quantity, quality, or otherwise. In other words, adding more of something may help the situation, but it takes more and more of that resource to generate the same increase in benefits as before. As a simple example, hiring workers to work in an empty factory may rapidly improve production, but over time the workers will begin to get in each other's way. This phenomenon is widely observed in economics, including in returns to capital, income growth across countries, and even research activity (Solow 1956; Mankiw, Romer, and Weil 1992; Kortum

1997; Bloom et al. 2020). In extreme cases, more of an input can make the problem worse. One such example, in software engineering, is given in *The Mythical Man-Month* (Brooks 1975).

Many AI models have also exhibited evidence of diminishing returns (Hestness et al. 2017; Kaplan et al. 2020; Zhai et al. 2022). While in some cases it is possible to improve the performance effect of an input (e.g., via new data-pruning methods; see Sorscher et al. 2022), these techniques typically do not change the underlying diminishing relationship (Muennighoff et al. 2023).

Just because the marginal value of each additional input tends to fall does not imply that performance is fundamentally limited. Adding more of every input—if they are available—can continue to produce substantial gains, as can finding new kinds of inputs (e.g., new kinds of data). And large enough changes in inputs may shift which class of algorithms or models perform best. For example, large language models became viable when sufficient data and computational resources became available, in turn spurring researchers to develop further technical innovations like transformer-based architecture or more specialized hardware (Vaswani et al. 2017; Bommasani et al. 2021; Dally, Keckler, and Kirk 2021). But the speed of continued progress is likely to be heavily dependent on the rate at which we continue to produce new innovations rather than simply by virtue of ever-increasing computational or data resources (Jones 2022; Philippon 2022).

Garbage In, Garbage Out

Data are key informational inputs into AI systems, and they are central to the way AI performs. AI systems make informed predictions because they use the correlations embedded in data. Many different changes have contributed to improvements in AI systems, including improvements in algorithms and increased availability of computational resources. Nonetheless, developers of AI-based prediction models continue to grapple with many of the same data-related challenges that statisticians and econometricians have faced for decades.[10] To understand AI technology as a whole, it is helpful to understand the unique role that data and data-related constraints play.

The scale and quality of available data directly affect the performance of AI, but a large quantity of data alone is not sufficient. Prediction models typically perform well in situations that look much like the data they are trained on. In contrast, rare or novel circumstances where the past is a poor guide to the future make prediction more challenging, as do data limitations

[10] These fields are very much related. Economists borrowed a large number of techniques from statisticians in the early days of econometrics; and in the late 1990s and early 2000s, many computer scientists adopted statistics and econometric techniques like Bayesian updating. While it can be challenging to collaborate because these different fields approach problems in different ways and have very different jargon, past collaborations have yielded substantial improvements.

that might not immediately be apparent. In situations with poor or incomplete data, models may be simultaneously highly confident and wrong in their predictions (e.g., DeVries and Taylor 2018). For example, concerns arise when input data are systematically biased. An AI system that is trained without accounting for the bias is nearly certain to reproduce it. Many current facial recognition applications face this problem, and an overreliance on AI facial recognition technology could exacerbate discrimination (e.g., Najibi 2020; Buolamwini and Gebru 2018; Raji et al. 2020a). (See box 7-1.) Additionally, in some instances, people may intentionally feed an AI system manipulated data so as to undermine its function (Shan et al. 2023). Such attacks can be more difficult to detect and reverse than more traditional methods of interference. After training is completed, isolating and removing the impact of poor-quality data can prove challenging and expensive, and may be only partially successful.[11] For all these reasons, curation of data is generally important for AI systems, just as it is for most technology firms.[12]

Data are unlike natural resources, such as iron or copper; they are often drawn from users. User data include things such as the words they publish in books or on social media, as well as records of the things they do, typically captured by now ubiquitous electronic devices. AI enables predictions to be individualized in ways that rules-based algorithmic approaches do not. Such personalization can allow firms to create customized products or recommendations, and these tailored products can benefit consumers. However, AI can also be used in ways that harm consumers through price discrimination, by suggesting products or services sold by the AI company that may not best meet a consumer's needs, or through the exploitation of behavioral biases (e.g., Gautier, Ittoo, and Cleynenbreugel 2020; Engler 2021). Many social media companies, for example, design their products to maximize engagement rather than entertainment or education, even when such engagement can be harmful (e.g., Luca 2015; Braghieri, Levy, and Makarin 2022). As consumers learn about AI-related targeting, they may abandon products or change their behavior, undermining the technology's value (e.g., Garbarino and Maxwell 2010; Nunan and Di Domenico 2022).

[11] Researchers continue to make progress on so-called unlearning methods to address the issue of unwanted data, though many approaches have been shown to have limited performance in practice (Kuramanji et al. 2023; Zhang et al. 2024). The implications of successful unlearning are also relevant for issues such as individual privacy protection (Neel and Chang 2023).

[12] In many cases, data have scaled up more quickly than firms' ability to curate them. While AI-powered curation may improve the situation, AI systems may also make the situation worse. For example, while some AI systems may help firms decide which content to publish, other AI systems may increase the volume of proposed content requiring review (Edwards 2023).

Box 7-1. AI and Equity/Discrimination

Many artificial intelligence applications use data generated by humans to predict how individuals will behave. While these data can give AI considerable power and utility, they also allow it to replicate many of humanity's worst biases. The capacity of AI to lead to discrimination—whether inadvertently or intentionally—poses new challenges for enforcement of existing anti-discrimination policies.

Economists have shown that discriminatory behavior can have many sources. Even in the absence of any intentional prejudgment (what economists call prejudice), discrimination based on statistical inference can be harmful (e.g., Lang and Spitzer 2020). Users of predictive algorithms have already faced this problem, including hiring managers who found they were favoring male candidates (Dastin 2018), potential employers who advertised job posts less heavily to women (Lambrecht and Tucker 2019), and health care systems that favored white patients over Black patients in predicting care needs (Obermeyer et al. 2019), among many other examples. These effects may arise from the biases of AI model developers, or inadvertently from previously unrecognized patterns in the data. The lack of transparency in sophisticated AI algorithms may compound the issue (e.g., Chesterman 2021; Hutson 2021). Even if AI providers remove obviously biased or prejudicial content from their training data, discrimination based on subtle statistical patterns is still likely (Barocas and Selbst 2016).

An additional challenge is ill intent among the users of AI models. AI's opaque methods could provide cover for prejudiced entities to use AI in numerous discriminatory ways, such as firms combining AI with surveillance to predict, deter, and punish union organizing activity, or landlords using AI to discriminate against potential tenants based on their predicted demographics. Evidence suggests that illegal behavior is already widespread in these contexts (McNicholas et al. 2019; Christensen and Timmins 2023), and users will likely adopt AI tools to continue their discriminatory practices and obfuscate their intent.

AI-abetted discrimination could harm individuals in the labor market, in housing markets, in financial transactions, and anywhere else predictive algorithms are used. Often, discrimination may only be observable through sophisticated analysis of AI methods and outputs. Regulatory measures to help identify discrimination in critical markets are necessary. The Biden-Harris Administration's Blueprint for an AI Bill of Rights emphasizes the importance of protection from algorithmic discrimination, and its recent Executive Order has identified key agencies within the Federal Government to develop the tools and issue guidance or regulations needed to combat it (White House 2022, 2023a).

Nonetheless, widespread AI adoption means that identifying and rooting out discrimination will remain an ongoing process. Researchers who study the auditing of AI algorithms generally conclude that a multifaceted approach is necessary, including a clear identification of objectives and metrics, transparency about the audit process, and a proactive consideration of how auditability can be incorporated into AI models in multiple stages (Guszcza et al. 2018; Raji et al. 2020b; Mökander et al. 2021; Costanza-Chock, Raji, and Buolamwini 2022). Explicit methods to identify discriminatory capabilities and strengthen AI guardrails are also likely to be a key component of a comprehensive antidiscrimination strategy (e.g., Ganguli et al. 2022). Some of these methods may themselves use AI, since predictive algorithms may be useful in detection of discrimination (e.g., Kleinberg et al. 2018). Reducing discrimination may also involve encouraging some forms of AI adoption. For example, algorithmic decision-making has been observed to reduce disparities in some lending contexts (Bartlett et al. 2022).

From the Technological Frontier to Reality

There are a number of different ways to measure the economic impact of a technology. How widely is it deployed? How does the production process change for existing products and services? What new products and services are created, and what old products and services decline or disappear? Of particular interest to economists and policymakers is the idea of productivity, the notion that we can do more with the same resources. Recent evidence suggests that large productivity increases driven by AI are possible in some specific contexts (e.g., Brynjolfsson, Li, and Raymond 2023).[13] And though such forecasts are notoriously challenging, economic analysts have already begun to update their forecasts to account for the potential of more rapid growth brought about by AI (e.g., Goldman Sachs 2023; Chui et al. 2023). A more fulsome answer to all these questions requires understanding not only AI's theoretical capabilities but also how AI systems might be used.

Adoption Is Difficult and Invariably Lags the Technological Frontier

Before a new technology can have real-world effects, it needs to be adopted by individuals and businesses. This process is costly and difficult, and thus the scale of adoption largely depends on weighing these costs against the potential benefits. AI has been an active area of computational research since the 1950s (Newell 1983), and many types of AI have been widely deployed (e.g., Maslej et al. 2023). At the same time, in many industries AI

[13] Precise measurement of productivity within firm environments can be challenging, but studies in controlled settings also suggest the potential for sizable productivity improvements in other contexts (e.g., Peng et al. 2023; Noy and Zhang 2023).

adoption has been low and has skewed heavily toward large and young firms (Acemoglu et al. 2022). In addition, some impressive advances in AI have been very recent, and it takes time for firms to observe progress and adapt.

Furthermore, technologies are rarely adopted at an even rate. Instead, early adoption is slow, as users and firms work through the challenges. It then proceeds more quickly as these challenges are overcome and economies of scale drive down costs (Hall and Khan 2003). Adoption can lag invention by decades, and differences in the surrounding circumstances can substantially change adoption timelines. For example, more than 90 percent of American households had microwaves within 30 years of their invention (Roser, Ritchie, and Mathieu 2023). In contrast, it was more than 100 years before flush toilets reached the same 90 percent threshold. Because the devices depended on running water, adoption was delayed until people had indoor plumbing.

Early adoptions of a technology often happen where it is least complicated to deploy. One of the earliest commercial AI success stories was in identifying credit card fraud. In this case, data were widely available, the key task clearly depended on prediction, the action to be taken was straightforward, and the costs and benefits of prediction quality could be readily quantified (Ryman-Tubb, Krause, and Garn 2018; Agrawal, Gans, and Goldfarb 2022). Similarly, in recent years, AI systems aimed at improving customer service have developed rapidly because the data were previously being collected, the functionality could easily be added to existing software, and customer service involves many low-complexity tasks (Xu et al. 2020; Brynjolfsson, Li, and Raymond 2023; Chui et al. 2023). These kinds of early projects using a technology have positive spillover effects for the technology as a whole, both because they are proof that the technology can be effective in a real-world setting and because they create valuable human capital—in the form of knowledge about how to adapt business practices to use the technology. The markets for AI are already adapting, with investment and start-up activity both increasing in recent years (Maslej et al. 2023). Businesses specializing in cloud computing and AI deployment have also since emerged, lowering costs and expanding adoption.

With AI, there are a variety of additional potential impediments to adoption—consider five. First, even when data are available to train an AI system, there may be additional data-related constraints on adoption. Many firms may not yet collect the necessary data for certain AI implementations, and they may face substantial challenges in beginning to do so. In other cases, systems do not receive feedback sufficient to judge the quality of their own predictions after they have been made. Finally, even when the data exist, legal restrictions like copyright may prevent their use.[14] Until these

[14] Copyright and other related issues are discussed in more detail later in this chapter.

data-related constraints on adoption are resolved, firms may have difficulty implementing AI. This likely explains some of the uneven adoption across industries and firms, as large firms are more able to invest in data collection and incumbent firms may not yet have completed their digital transformation (Verhoef et al. 2021).

Second, because predictions can be wrong, AI systems introduce an additional kind of risk. Risk is often a major factor in technology adoption; when stakes are high, risk-averse firms may be less willing to make needed investments or use inputs with uncertain returns (Roosen and Hennessy 2003; Whalley 2011).[15] Often, the distribution of potential payoffs for business decisions is not just uncertain but also ambiguous, in that firms do not know the potential set of outcomes and their probabilities. Ambiguity makes prediction more difficult, and research has shown the condition has a range of effects on firms' willingness to develop or adopt new technologies (Knight 1921; Beauchêne 2019). Risk and ambiguity related to liability assignment is a prominent example discussed later in the chapter.

Third, many potential AI applications exhibit network effects, in which the use of the technology by one party increases its value to others. One way in which these network effects can arise is by increasing the amount of feedback data from users, which in turn increases the quality of predictions for everyone (Gregory et al. 2021). Adoption can also lead to network effects by reducing coordination costs, such as vehicular communications systems that simplify the set of predictions that autonomous cars would need to make if they were widely adopted (Arena and Pau 2019).

Fourth, integrating AI systems with humans has unique challenges related to incentives, job design, and communication. For example, some processes may work best when AI systems handle routine decision-making, like highway driving, and humans handle unusual situations, like construction zones. But without guardrails, the human may be tempted to leave too much to the AI system or may accidentally fail to intervene (e.g., fall asleep at the wheel) (Athey, Bryan, and Gans 2020; Herrmann and Pfeiffer 2023).

Fifth and finally, permanent or indefinite limits to AI's adoption are possible for many reasons, including those unrelated to the technology. Institutional quality issues, coordination problems, and financial frictions can all delay or halt technological adoption (e.g., Parente and Prescott 1994; Foster and Rosenzweig 2010).

[15] Some scholars have argued that the fields of AI and machine learning have a serious problem with reproducibility because of the complexity and nuances of the problems, which may provide a further incentive for firms to delay adoption (Kapoor and Narayanan 2023).

AI Has the Potential to Be Even More Transformative in the Future

In the past, many innovations' biggest effects came from enabling people to structure entire productive processes differently and from spurring complementary inventions, not from performing individual tasks at a lower cost (David 1990; Brynjolfsson, Hui, and Liu 2019; Agrawal, Gans, and Goldfarb 2022). Consider the migration of factories from steam power to electricity. Steam power required vertical factories oriented around shafts used to power machines. Even when electricity became less expensive than steam power, adoption remained slow and unsteady because replacing the machines was capital intensive for only a modest ongoing benefit. In the long run, the largest gains from electricity were not from direct cost savings, but rather arose because firms were no longer required to locate their factories next to steam plants or design them vertically (Du Boff 1967). Realizing these gains, however, required building entirely new factories and power plants, and developing complementary technologies, all of which required even more capital and time. Similarly, the widespread adoption of automobiles and subsequent construction of the interstate highway system did not just increase the number of car trips consumers took; it changed where people lived (Biggs 1983; Eschner 2017).

AI is a general-purpose technology (GPT), like electricity and computers (Brynjolfsson, Rock, and Syverson 2021). Key hallmarks of these technologies are that they improve over time and lead to complementary inventions (Bresnahan and Trajtenberg 1995). Because of these similarities, the effects of AI are also likely to be larger and more wide-reaching than the initial use cases would suggest. While some services have been redesigned on the basis of AI, and some new technologies have been built with AI from the ground up, many systems and processes that could be redesigned to take advantage of AI have not yet been updated (McElheran et al. 2023). Firms that invest in AI are showing signs of increased product innovation, but they do not yet show evidence of process innovations that might arise from a more thorough restructuring of their operations (Babina et al. 2024).

In addition, AI technology continues to evolve in transformative ways. For example, many recent developments in AI have come not from increasingly specialized models but rather from foundation models, which are trained on very large volumes of data and are adaptable to many different tasks (Bommasani et al. 2021). This stands in seeming contrast to one of the earliest and best-known ideas in economics: that gains from specialization are a fundamental force behind economic growth (Smith

1776; Ricardo 1817).[16] However, a further investigation suggests that the rise of broad foundation models is consistent with the same forces that yield specialization in other contexts. Gains from specialization are bounded not only by the size of markets but also by training costs, transaction costs, the need for workers to synchronize, and other frictional forces in the economy (Becker and Murphy 1994; Bolton and Dewatripont 1994; Costinot 2009). The degree of specialization ultimately depends on how these costs compare with the potential benefits: if costs are high, then relatively little specialization is likely to occur. In the case of AI-induced automation, coordination costs between computer systems are often low compared with coordination costs between humans, especially as the scale increases. However, training costs for foundational AI models are currently high, which likely limits overall specialization. One way to reduce such costs is to train models on targeted subsets of data (e.g., Kaddour et al. 2023), but many such applications may not yet make economic sense. Another approach is to fine-tune models in specialized ways after their initial training (Min et al. 2023).

This approach is widely used, but research is ongoing as to how effective this method is compared with or in concert with specialization at the training stage (e.g., Kumar et al. 2022). In addition, as discussed earlier in the chapter, some systems continue fine-tuning after deployment, though updating models over time may cause them to behave in unpredictable ways (e.g., Chen et al. 2022; Chen, Zaharia, and Zou 2023). Finally, specialization may be integrated in more limited ways—for example, through multitiered production processes with generalized and specialized components (Garicano 2000; Ling et al. 2023). The outcomes from ongoing AI research in these areas may have large implications for future AI adoption, market structure, and competition; later in this chapter, there is further discussion of AI market structure and competition. Alternatively, decreases in computational costs or other methodological improvements may make specialized generative models more economically viable over time (e.g., Leffer 2023).

Finally, AI may also drive changes outside the markets where it is directly employed. In some areas, AI may allow automation of a wide variety of tasks that might not have historically been regarded as prediction-centered. For example, farmers can make conditions more hospitable for bees to increase plant pollination, and researchers are attempting to create AI-powered robotic pollinators for this purpose (Cherney 2021). Conversely, just as automobiles undermined the buggy whip industry (Levitt 2004) and smartphones have decreased demand for printed maps, technology can make

[16] Subsequent research has identified specific economic mechanisms that encourage specialization, such as differences in inputs or skill endowments, gains from human capital deepening, and consumer tastes for variety (Krugman 1981; Ohlin and Heckscher 1991; Becker and Murphy 1992). Similarly, AI researchers have identified cross-country patterns of comparative advantage as one reason AI might be specialized (Mishra et al. 2023).

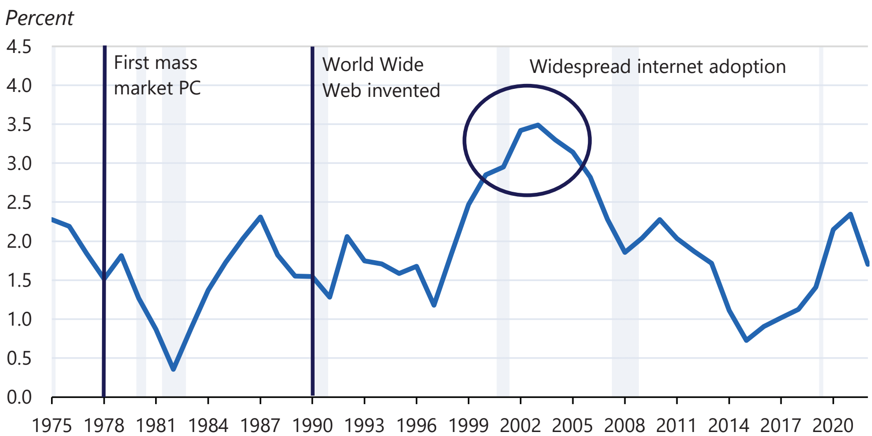
products obsolete. In this case, AI may partially or entirely eliminate the need for products that exist primarily due to insufficient prediction capabilities. For example, many stores and warehouses carry substantial inventories because they are unable to predict what customers will demand. If improved prediction capabilities can substantially reduce the need for such storage, there may be substantial reductions in the necessary land and infrastructure. In short, AI may increase consumption of some products and decrease consumption of others. This same dynamic, complementing in some places while substituting in others, is also important in the labor market, and is further explored later in the chapter.

When Will We Know the Future Has Arrived?

The scale and scope of AI's effects on the economy will be influenced by the development and adoption issues discussed earlier in the chapter. But even after invention and adoption, there can be substantial delays before a technology's effects are captured in macroeconomic statistics like productivity. Thus, there is still considerable uncertainty—not only about when the future effects of AI will be felt but also when economic statistics will reflect them.

In 1987, the Nobel Prize–winning economist Robert Solow said that computers were everywhere except in the productivity statistics. As figure 7-3 shows, faster productivity growth actually did appear in the data, just not until roughly two decades later, during a period of widespread Internet adoption. Thus, it is uncertain whether the productivity increase was simply delayed or whether the invention of a complementary technology was a

Figure 7-3. Nonfarm Labor Productivity Growth, 1975–2010 (5-year moving average)



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Sources: Bureau of Labor Statistics; CEA calculations.
Note: Gray bars indicate recessions.
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necessary prerequisite. Productivity also eventually returned to its earlier trend, which suggests that it was more of a level shift than a structural growth shift. Consistent with past experience, current productivity statistics do not suggest an immediate uplift in productivity resulting from AI.

Some have argued that instead of a delayed effect, this pattern is the result of a measurement issue common to general-purpose technologies (Brynjolfsson, Rock, and Syverson 2021). These technologies initially require large investments, particularly in intangible and thus unmeasurable assets like new business practices and employee knowledge. Investments in a new technology may also crowd out other productive work or other potential productivity-increasing investments. As a result, there may be a considerable period when expenditures are measured but benefits are not.

Ultimately, the evidence is inconclusive. It may be a while before the full effects of AI are felt, and even longer before we can confidently observe it in economic statistics. Moreover, a productivity boom is not guaranteed. The current excitement over generative AI may fade if developers and users discover that its drawbacks are insurmountable, if few new data are available to power improvements, or if it turns out to be difficult to monetize the technology. Furthermore, how deeply AI becomes integrated into the economy depends not only on technological progress but also on institutional and regulatory issues. These topics are discussed more fully later in this chapter. (See box 7-2.)

Box 7-2. Government Applications of AI

One way that AI can increase productivity and improve individuals' well-being is by using it to improve the Federal Government. Numerous administrative and regulatory processes could benefit from the adoption of AI. The recent Executive Order directs agencies throughout the government to identify and implement beneficial uses (White House 2023a). The order also encourages agencies to take steps to attract and retain the AI talent necessary for adoption to take place.

Prediction, evaluation, and routine content generation are core components of many government processes. Often, these tasks are performed via labor-intensive methods, and AI could make these operations more efficient by automating their most routine components. Applications for government benefits are one such example. Most applications for benefits do not involve fraud, and many can be processed with little human labor. However, application reviews must be thorough enough to detect and disincentivize fraudulent activity, and so considerable human labor is used. Thoughtful application of AI could improve fraud detection in two ways, by detecting fraud directly, and by filtering and processing clearly non-fraudulent applications so that employees can more effectively target their fraud-detection efforts.

Government AI adoption will look different than private sector adoption because of the unique challenges the government faces. For example, private firms are often not required to protect privacy and confidentiality to the same extent as the Federal government (e.g., GAO 2018). Performance standards that would be acceptable in a commercial environment may be insufficient for sophisticated or sensitive government applications. In addition, many government activities simply have no private sector analog. Commercial solutions and private sector innovation will undoubtedly play a role in government AI adoption, but the government may only realize the full benefits of AI by tailoring applications to suit its unique needs.

Another reason to encourage government AI adoption is that positive externalities are likely to result. Government innovations have a long history of being repurposed to benefit other sectors of the economy. Many current AI applications are only possible because of technologies like GPS that arose from government research and development. Private sector AI innovation has been rapid in recent years, but numerous limitations remain. The government is well positioned to be a leader in developing solutions to outstanding problems precisely because it faces so many unique situations.

Institutions such as the Defense Advanced Research Projects Agency (DARPA) have long embodied a model of mission-focused innovation to considerable success (e.g., Bonvillian 2018). Similar research agencies are found throughout the government and are already engaged in targeted AI research. However, potential AI applications are dispersed throughout many organizations, and spillovers between agencies tackling similar problems are likely. New interagency councils along with existing cross-government programs such as the U.S. Digital Service are an initial step to ensuring that knowledge sharing within the government remains a priority.

Government adoption of AI is not without risk. For example, automating too many processes too quickly could result in a lack of accountability and access to key services, in addition to public sector job losses. But with these risks comes the opportunity for the government to lead by example. Adoption that is done thoughtfully, with input from current workers and other stakeholders, will lead to better outcomes and allow the government to develop the key institutional knowledge necessary to create good policy (Kochan et al. 2023).

AI and the Labor Market

What does AI's ability to undertake tasks previously performed by humans mean for labor and the labor market? On net, will AI complement workers, yielding increased jobs, productivity, and prosperity? Or will prediction models substitute for human labor, yielding a world where fewer people are needed to work, but also where fewer people can contribute to the economy while also earning a living?

Although AI is a comparatively new technology, the notion of "technological unemployment" is hundreds of years old. Numerous 18th- and 19th-century economists hypothesized that technology would displace workers by substituting for their labor (Mokyr, Vickers, and Ziebarth 2015). During the Great Depression, John Maynard Keynes predicted that within a century, individuals would work no more than 15 hours a week, and that the innate desire to work would lead to many workers performing small tasks so they could remain at least nominally employed (Keynes 1930).[17]

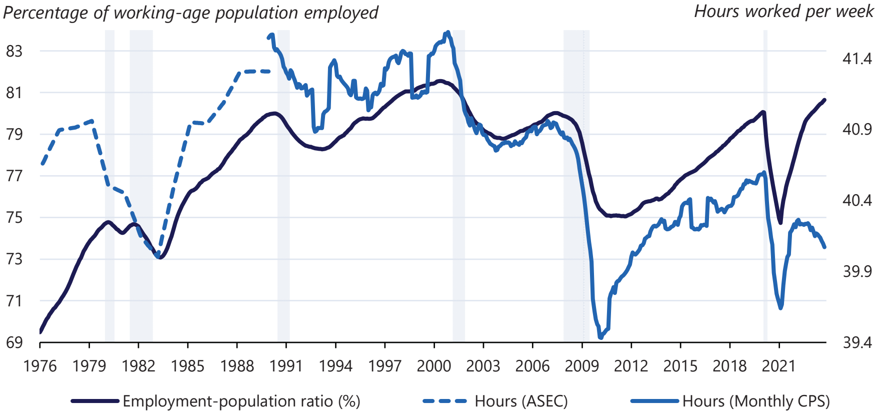
Figure 7-4 shows that so far, these predictions have not proven true. Prime-age labor participation remains near long-term highs, matched only by a brief period in the late 1990s. The average prime-age worker has worked close to 40 hours a week for decades. Some have noted that increased life spans have reduced overall time spent working over the life cycle, and that working conditions have improved considerably (e.g., Zilibotti 2007). Nonetheless, while Keynes accurately predicted massive average income increases, he failed to recognize how ever-increasing demand for consumer goods and other forces would keep people from working fewer hours.[18]

This historical evidence suggests that caution is warranted in making predictions about technology's impact on the future of the labor force. Moreover, mistaken predictions in this area have not been random: They have overwhelmingly incorrectly predicted substitution instead of complementarity (Autor 2015). To be fair, the adaptations of workers and firms to technological change and increased wealth are difficult to foresee.

[17] CEOs and Nobel laureates have recently made nearly identical predictions about AI shortening the work week (Taub and Levitt 2023; Rees 2023).

[18] Economists have highlighted many features of the economy that may discourage workers from reducing their hours despite higher average incomes over time. Relative product quality or status comparisons may lead consumer demand to track higher purchasing power (e.g., Frank 2008). Increased wage inequality may be associated with an increase in the return to additional hours of work (e.g., Freeman 2008). Performance-related compensation systems and increased competitive pressures may make hours reductions more costly (Freeman 2008). Increasing income volatility may lead individuals to increase their labor supply as insurance against future economic shocks (Heathcote, Storesletten, and Violante 2010). Changes to work attributes may have made time spent at work more pleasant, and individuals may value the social or intellectual components of work (e.g., Cowen 2017). Nonetheless, recent empirical evidence from inheritances and lottery winners in the United States suggests that the work-reducing impact of greater wealth is substantial, and is stronger among individuals with higher incomes (Brown, Coile, and Weisbenner 2010; Golosov et al. 2021).

Figure 7-4. Employment-Population Ratio and Weekly Work Hours, 1976–2022



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Sources: Current Population Survey; Bureau of Labor Statistics; CEA calculations.

Note: CPS = Current Population Survey; ASEC = CPS Annual Social and Economic Supplements. Working-age population refers to the population between the age of 25 and 54 years. The employment-population ratio is a 12-month moving average. ASEC hours are a measure of hours worked in the last week. Monthly CPS hours are a measure of hours worked in the last week from the basic monthly CPS. Gray bars indicate recessions.

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Still, technological change has greatly affected workers over time through their occupations, the tasks they perform, and the payment they receive. Economic frameworks characterize the forces behind these prior effects, and in doing so they also provide suggestive evidence of the impact that AI may have in the future.

In the next subsection, the CEA considers several leading frameworks used by economists to study the impact of technological change in recent decades. Although data limitations make it difficult to attribute this impact to individual technologies, predictions from these frameworks align with the observed patterns of economic change stemming from the widespread adoption of general-purpose technologies like computers and the Internet.[19] A common theme among these frameworks is that technologies make an impact on different groups of workers differently, in large part because they perform different tasks. The ability of AI to perform additional tasks may mean that its effects will differ from the effects of automation in the past.

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[19] Technologies tend to be adopted in the circumstances where they are especially valuable, and multiple technologies tend to be in use simultaneously; these features make isolating a single technology's effects difficult or impossible in most circumstances without further assumptions. In one well-known example, researchers found that they could not empirically distinguish the purported large effects of the computer from the effects of the pencil (DiNardo and Pischke 1997). In limited cases, researchers can exploit exogenous variation in adoption brought about by other policies to help isolate the impact of a specific technology. For example, this approach has been used to suggest that broadband Internet adoption complements workers performing abstract tasks, and substitutes for workers performing routine tasks (Akerman, Gaarder, and Mogstad 2015).

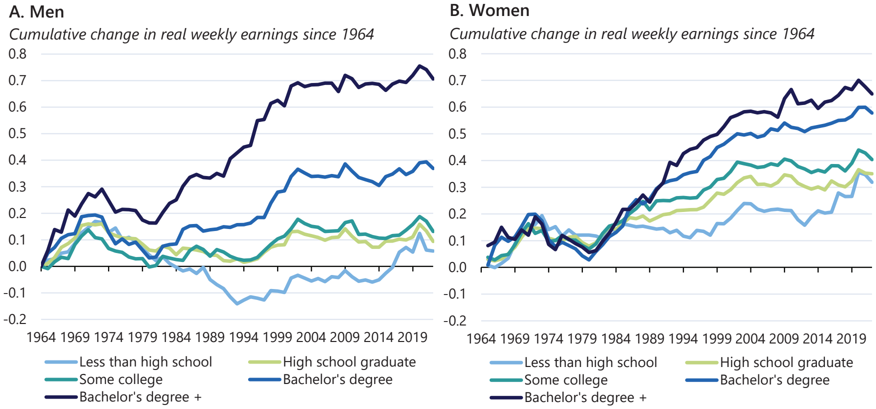
In response to this concern, the CEA uses information about the current task content of occupations to provide suggestive evidence about the occupations and workers that may be affected by AI in the future. As noted throughout, the analysis presented has similarities to other analyses found in the recent literature. The CEA's measure of occupational AI exposure is closely related to and extends the recent analysis by the Pew Research Center (Kochhar 2023), and many of its conclusions are similar. However, all predictions of the future are inherently speculative, because they are based on the models and data that exist today. The assumptions that go into this analysis may later prove to be erroneous. And many open questions cannot yet be answered, or cannot be answered with the available data. The particular concern of data limitations is discussed later in the chapter.

Modeling the Effect of Technological Change on Labor Markets

Though technological changes are often complex, a simple framework can often explain their effects on employment and earnings. The model of skill-biased technological change (SBTC) is one influential example. This model is based on the notion that technology increases the relative demand for highly educated workers over time (generally proxied by a college education). The SBTC model conceives of "skill" very narrowly, and it abstracts away from other features of labor markets such as unemployment. The benefit of these simplifications is that they allow the model to succinctly describe the relationship between technological change and wage patterns: When the relative demand for highly educated labor grows more quickly than the relative supply of labor from highly educated workers, the relative wages of these workers rise compared with those of workers without college degrees. This model suggests that the growing college wage premium over the past several decades is a result of demand for educated workers increasing faster than their supply. Skill-biased technological change is sometimes characterized as a race between education and technology; the more technological change outpaces the supply of educated workers, the more workers' wages rise (Goldin and Katz 2007).

Figure 7-5 demonstrates this point; inflation-adjusted weekly earnings for working-age men and women with graduate degrees have risen more than 60 percent since 1964, while earnings for workers with less education have increased more slowly. In fact, 75 percent of the rise in earnings inequality from 1980 to 2000, measured as the log of hourly wage variance, can be explained by the increase in the college wage premium alone (Autor, Goldin, and Katz 2020). Figure 7-5 also shows that a model of ever-increasing demand for highly educated labor is incomplete; the flatness of the college premium over the last two decades, especially for men, and the comparatively rapid wage growth among those who did not receive a

Figure 7-5. Cumulative Changes in Real Weekly Earnings by Education for Men and Women



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Sources: Current Population Survey; CEA calculations.

Note: Data are cleaned and analyzed following Autor (2019). Full-time, full-year workers between the age of 18 and 64 are used and education categories are harmonized using the procedures described by Autor, Katz, and Kearney (2008). All earnings are deflated by the chain-weighted (implicit) price deflator for personal consumption expenditures.

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high school degree over the past decade, do not align with a purely demand-driven SBTC explanation.

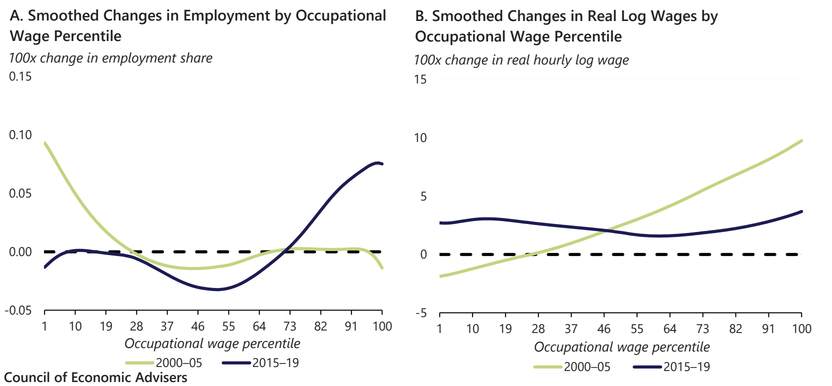
The SBTC framework is hampered by two limitations: (1) it conceives of "skill" as a one-dimensional attribute, typically proxied by education, and (2) it does not explain why technological change increases the relative demand for educated workers. As an example of the first limitation, the SBTC framework would classify workers in occupations like stenographers, typists, and paralegals similarly, based on their average level of educational attainment. However, following personal computer adoption, paralegals saw both earnings and employment rise (i.e., demand for the job increased), while typists and stenographers saw their employment dwindle. In contrast, many occupations that require manual labor (e.g., roofers) perform their work much as they have for decades, with relatively stable employment and modest real earnings growth in recent years. These distinctions are especially salient when considering AI's predictive and generative capabilities; jobs that rely on predictions or routine generation are more readily affected by AI than others that do not involve these tasks.

To overcome the limitations of the SBTC model, researchers have suggested an alternative framework that uses a richer notion of workers' characteristics, categorizing workers by the task composition of their occupations (Autor, Levy, and Murnane 2003). Such models typically divide tasks along two characteristic dimensions: whether they are routine or nonroutine and whether they are manual or analytic. Technological change has led to the automation of many routine tasks. Workers who performed these tasks have seen their employment and earnings opportunities decline.

Workers performing nonroutine manual tasks have been less affected by recent technological changes, while those performing nonroutine analytic tasks have been made more productive, as technology complements their work. Because the workers performing nonroutine tasks are often at the extremes of the earnings distribution, while workers performing routine tasks are often in the middle, the model suggests that technology can cause labor market polarization.

Research finds evidence of U-shaped job polarization in employment and earnings, particularly for the 1980–2005 period (Autor and Dorn 2013).[20] Evidence also suggests that polarization happens inconsistently over short periods, with employment and earnings growth often concentrated on one side or another of the occupational wage distribution (e.g., Mishel, Shierholz, and Schmitt 2013). Figure 7-6 shows that during the period of peak productivity growth in the early 2000s, most employment growth was near the bottom of the occupational wage distribution, even as real earnings declined among that same group. In contrast, more recent data from 2015 to 2019 show quite different growth patterns.[21] Nearly all growth in employment shares occurred in the top quintile of occupations, and real earnings growth was broad based, though slightly stronger among low-earning occupations than others.

Figure 7-6. Smoothed Changes in Employment and Earnings Across Occupational Wage Distribution



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Sources: American Community Survey; CEA calculations.
Note: Following Autor and Dorn (2013), occupations are ranked by initial mean wage and are grouped into percentiles weighted by aggregate hours. Analysis uses full-time, full-year workers between the age of 18 and 64.
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[20] While this pattern is often attributed to computerization, other research has suggested that the pattern may have begun even earlier, and that it could be linked to a broader shift from manufacturing to services employment (Bárány and Siegel 2018).

[21] The CEA ends its analysis of employment and earnings changes across the occupational distribution in 2019 because of the lingering effects of the COVID-19 pandemic in more recent data.

Both periods show employment share reductions at the middle of the earnings distribution, aligning with a core task-based model prediction. The patterns also suggest a nuanced interpretation of the SBTC model. The rapid adoption of computers and information technology in the early 2000s appears to have increased demand for workers in high-wage occupations more rapidly than their available supply could adjust. The pattern of strong demand for high-wage workers has continued; but in recent years, the supply of workers to these occupations has also grown more rapidly. The proportion of the population age 25 years and above who have completed at least four years of college increased by 12 percentage points from 2000 to 2022, from 26 to 38 percent (Census 2023). Even as job polarization has pushed workers into occupations at the earnings distribution extremes over some periods, relative supply's ability to catch up with relative demand in recent years has enabled increasingly stable earnings growth across the earnings distribution. The patterns also suggest that if AI continues or intensifies the trend of strong demand growth for high-wage workers, then continued rapid supply growth will be necessary to sustain broad-based earnings gains.[22]

Modification and additions to this task-based framework have recognized that occupations and tasks are not static. In 2018, more than 60 percent of employment was in jobs that did not exist in 1940 (Autor et al. 2022). New work tends to be concentrated in cities and in occupations with higher average levels of education (Lin 2011; Autor et al. 2022). As new technologies emerge, workers begin performing entirely new tasks, gaining a comparative advantage by complementing the technology. Some tasks cease to be performed by humans, but the new tasks can keep people employed even in the face of rapid technological change. Instead of a race between education and technology, the "new task formation" framework characterizes the labor market as a race between human and machine (Acemoglu and Restrepo 2018).

The new task formation framework is especially promising for understanding AI and other recent technological shifts. For example, the framework is robust enough to explain why few people now work as telephone operators, while data scientist and wind turbine service technician are among the occupations projected to grow fastest in coming years (Price 2019; BLS 2023). It also explains why the share of total income going to workers has declined in some recent periods of technological change but has

[22] Conversely, AI could make training workers easier in ways that moderate this pattern. For example, Brynjolfsson, Li, and Raymond (2023) find that the largest productivity gains in their context came from improvements among novice or less skilled workers. It may be that in this context, current AI systems are most useful for training such workers. Furthermore, it may be that an AI system trained on data from existing workers is simply unable to do better than the best of those existing workers.

risen at others: Technology automates and creates new tasks simultaneously (Acemoglu and Restrepo 2019).

Occupation-Specific Effects of AI

The technological change literature discussed above generally concludes that technology affects workers through a mix of complementarity and substitution. Some workers typically benefit from technological change, either because the evolving technology provides new labor market opportunities for them or because it enhances their productivity in their current job. Conversely, some are harmed, typically due to job displacement. Predicting the impact on a given occupation requires identifying whether it is exposed to AI via its particular mix of activities, and also whether, on net, AI complements or substitutes for human performance of those activities.

Researchers have made several attempts to identify and explore the occupations AI is most likely to affect. Surveying individuals about what they expect is one approach. A second approach is to classify occupations by task or activity content (e.g., Frey and Osborne 2017; Felten, Raj, and Seamans 2021; Brynjolfsson, Mitchell, and Rock 2018; Kochhar 2023; Ellingrud et al. 2023). Other researchers have compared the results of this approach to an AI system's predictions of what its own impact will be (Eloundou et al. 2023). Each approach is limited in its ability to measure and predict AI's impact on future economic activity. For example, the occupational content measures used by these papers are generally retrospective and are not necessarily based on actual exposure to deployed AI. No single measure should be considered definitive.

The CEA begins its analysis by considering the specific activities performed in each occupation, and the importance of these activities for the occupation. The Department of Labor's Employment and Training Administration collects this information as part of its O*NET (n.d.) database. The CEA follows the Pew Research Center (Kochhar 2023) in identifying 16 work activities with high exposure to AI. CEA researchers then construct a measure of these activities' relative importance compared to all other work activities.[23] The measure is then used to identify a subset of occupations in which AI-exposed activities are particularly central to the performance of the work. Workers in such occupations are plausibly the

[23] Although the CEA identifies the same AI-exposed work activities as Pew, the relative importance measure used by the CEA differs slightly. In particular, it relies on normalizing the importance scales for each activity across occupations, then measuring relative importance as the difference between the average normalized importance of AI-exposed activities and all other activities. Following Pew, the top 25 percent of occupations according to the measure are identified as AI-exposed. Among these occupations, AI-exposed work activities are at least 0.25 standard deviation more important to the performance of the occupation than the average for other activities.

ones most likely to be affected by AI, whether positively through complementarity, or negatively through substitution or displacement.[24]

To explore the potential for complementarity versus substitution, the CEA also considers a key feature of automation: Labor-substitution is easiest and cheapest in situations where complexity and difficulty are low. Working with AI in a complementary fashion may be more effective in complicated and challenging jobs.[25] The CEA captures the distinction by using responses to a separate O*NET question about the degree of difficulty or complexity at which each work activity must be performed for each job. Survey respondents are asked to indicate the level of activity performance requirements for their job, and are provided reference anchors that characterize the difficulty and complexity associated with different levels.[26] CEA researchers then divide the set of AI-exposed occupations into two groups based on whether their performance requirements for AI-exposed activities are above or below the average across all occupations. Although this measure is coarse, it reflects the underlying relationship between the difficulty of an activity and its ability to be fully automated.

These measures of occupation-level exposure and potential for substitution allow the CEA to study AI's potential effects across the earnings distribution, demographic groups, industries, and geographic regions. The CEA's analysis examines the occupations most likely to be exposed to AI in comparison with all other occupations. However, there are important differences within high and low exposure and activity performance categories from which this analysis abstracts, and the results are contingent on the exposure threshold chosen.[27] As such, while this approach provides some important insights about who is more or less likely to be affected, it does not tell us how widespread these effects will be on the labor market as a whole.

[24] In addition to affecting levels of employment and earnings, AI could affect job quality in numerous ways. The potential for occupations to experience these changes is also likely correlated with the exposure measure presented here.

[25] Task or activity complexity has been shown to complicate decision-making and increase its information demands, which may determine automation possibilities (e.g., Byström and Järvelin 1995; Sintchenko and Coiera 2003). Recent research has also suggested that task complexity plays a role in whether AI is adopted for activities such as customer service and medical decision-making (Fan et al. 2020; Xu et al. 2020). Other recent research on AI exposure has suggested that potential complementarity can be measured using other O*NET information on work contexts and job zones (Pizzinelli et al. 2023).

[26] The O*NET questionnaire asks respondents to report the activity performance level needed to perform their job on a 7-point scale, with benchmarks at the low end, midpoint, and high end. For example, in the AI-exposed activity "Evaluating Information to Determine Compliance," "Review forms for completeness" scores a 1, "Evaluate a complicated insurance claim for compliance with policy terms" receives a 4, and "Make a ruling in court on a complicated motion" scores a 6. See Peterson et al. (1995) for further details on the survey design.

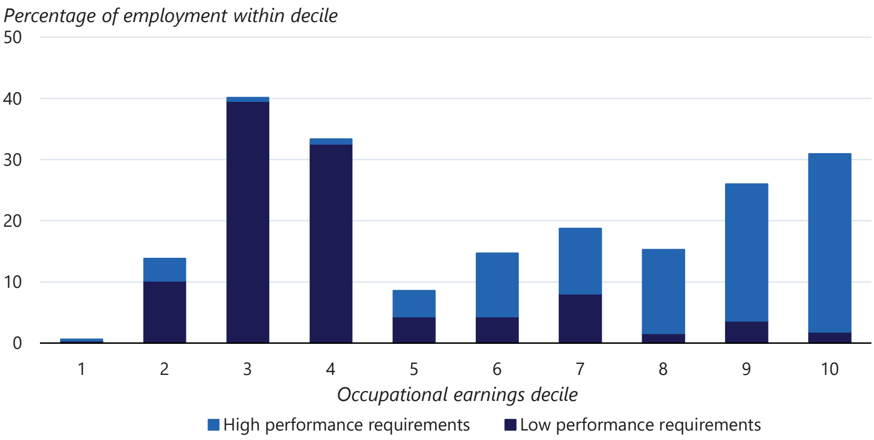
[27] The percentage of employees who are exposed to AI directly depends on the threshold chosen. However, the CEA's analysis suggests that the economic and demographic distribution of effects is relatively insensitive to that choice.

With this caveat in mind, figure 7-7 groups occupations into deciles based on the average earnings of workers, and then reports the percentage of workers within each decile who are employed in AI-exposed occupations. Similar to the task-based model's predictions, employment exposure is not monotonic. The most significant AI exposure levels correspond to occupations in the lower-middle portion of the earnings distribution, in the third and fourth deciles. However, more than a quarter of workers in the top two deciles are employed in AI-exposed occupations as well.

The addition of information about the required level of activity performance adds additional context regarding possible complementarity or substitution. Although AI-exposed activities are relatively central to each examined job, individuals in high-earning occupations are more likely to be required to perform AI-exposed activities at a higher level of complexity or difficulty than those in low-earning jobs. Because implementing AI as a human substitute is more costly and/or challenging for complex and difficult tasks, the analysis implies that AI may more quickly be able to substitute for employment in the lower-middle portion of the earnings distribution. To the extent that workers in some occupations can work in conjunction with AI to raise their productivity, the analysis provides suggestive evidence that such occupations may already have higher-than-average wages.

In figure 7-8, CEA researchers examine AI exposure across demographic groups. Previous research has suggested that AI exposure increases with education, that it is least concentrated among young workers, and that

Figure 7-7. Employment in High-AI-Exposed Occupations by Earnings Decile



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Sources: American Community Survey; Department of Labor; Pew Research Center; CEA calculations.
Note: Deciles are calculated using mean occupational earnings of workers who are full-time, full-year workers age 16 plus. Performance requirements are captured using the O*NET data measuring degree of difficulty or complexity at which a high-AI-exposed work activity is performed within an occupation. High (low) indicates an average degree of difficulty above (below) the median.
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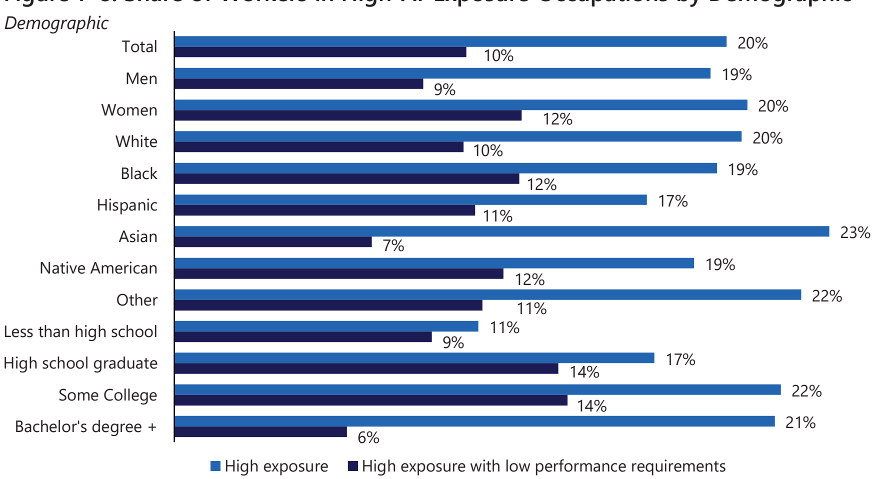
it is somewhat more prevalent among women, as well as among white and Asian workers (Kochhar 2023). Using its own occupation-level exposure metric, the CEA largely replicates these findings. As in figure 7-7, the CEA considers how AI-exposed workers whose jobs have lower performance requirements differ from AI-exposed workers as a whole. This analysis suggests that the demographic characteristics of workers negatively affected by AI may be somewhat different from those of individuals simply exposed to AI. For example, many high school graduates lacking four-year degrees have jobs that are highly AI exposed and that have relatively low performance requirements. A similar fraction of college graduates are exposed to AI, but their performance requirements are higher on average, and so they may be less at risk of displacement. Similarly, while women are only slightly more exposed to AI than men, they are more likely to have high exposure with low performance requirements, suggesting that women may be at higher risk of displacement.

The findings shown in figures 7-7 and 7-8 suggest that AI may be a skill-biased technology, increasing relative demand for workers with high levels of education in high-earning occupations. They also suggest that AI could exacerbate aggregate income inequality if it substitutes for employment in lower-wage jobs and complements higher-wage jobs. The possibility of increased inequality from AI has been widely discussed among economists studying the topic (e.g., Korinek and Stiglitz 2018; Furman and Seamans 2019; Acemoglu 2021). However, such an interpretation of the

Figure 7-8. Share of Workers in High-AI-Exposure Occupations by Demographic



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Sources: American Community Survey; Department of Labor; Pew Research Center; CEA calculations.
Note: Analysis uses full-time, full-year workers age 16 plus. Performance requirements are captured using the O*NET data measuring degree of difficulty or complexity at which a high-AI-exposed work activity is performed within an occupation. Low indicates an average degree of difficulty below the median.
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evidence presented here should be made cautiously. As the historical analysis given earlier in the chapter demonstrates, supply-and-demand forces both play a role in determining patterns of wages and employment. Nonetheless, the possibility of increased inequality resulting from AI adoption may inform policy responses.

More generally, the economic and demographic breakdowns of figures 7-7 and 7-8 suggest possible effects, but they simplify a complex reality. For example, figure 7-8 does not imply that the 10 percent of workers who have high AI exposure and low performance requirements will inevitably lose their jobs. Rather, the measures shown identify the occupations and workers who perform the tasks that are most likely to change as a result of AI. The implications for jobs and workers may be quite nuanced.

For example, most jobs remain a collection of tasks of which only a portion can be automated. AI may allow humans to focus on other tasks, fundamentally changing their jobs without reducing the use of their labor. For example, if AI eventually allows school buses to drive themselves, children may still need someone on the bus to watch them, ensure they behave, and ensure they enter and exit safely. In other words, AI-led automation might fundamentally change the school bus driver's job, but it is unlikely to eliminate the job. Similarly, airplanes still have pilots, despite autopilot systems having automated some of their tasks for more than a century (Chialastri 2012).

Additionally, even among workers within an occupation, the extent of automation may be highly context dependent. Different AI models may be deployed in different situations, tailored to unique goals in ways that allow them to succeed at different tasks. An AI model that can replace human performance of tasks in some contexts might require extensive human assistance in others, or it may not be economically viable to adopt (e.g., Svanberg et al. 2024).

More broadly, there are reasons to believe that integrating humans and AI may often prove more effective than using either alone. Having multiple approaches to prediction and problem solving often produces better results than any one approach on its own. Diversity of thought can improve human decision-making (Post et al. 2015), and prediction techniques may benefit by combining multiple different machine learning approaches (Webb and Zheng 2004; Dong et al. 2020; Naik et al. 2023). Emerging research suggests that this principle extends to the combination of human and AI approaches as well (Zirar, Ali, and Islam 2023; Hitsuwari et al. 2023).

Finally, these measures of AI exposure are based on the tasks that future AI systems are believed to be well suited to perform. As AI technology develops, it may change in ways that lead it to automate a different set of tasks than existing measures foresee.

A more precise understanding of how AI affects specific occupations, industries, demographic groups, and geographic regions will be critical for constructing appropriate policy responses. Researchers continue to develop and refine their frameworks to predict the potential effects of AI. As evidence of AI's effects emerges, these frameworks will evolve to incorporate the new information. At the same time, the limitations of available data and testable frameworks will continue to constrain researchers' quest for understanding.

Evidence for AI's Effects

Economists have already begun measuring AI's adoption, and they are looking for signs of its impact on the labor market. Although uncertainty remains, some patterns have emerged. First, AI adoption is driven by larger and more productive firms. While the percentage of businesses adopting or integrating AI directly is still small, these firms employ a sizable share of workers (Acemoglu et al. 2022; Kochhar 2023). Note that survey measures of technology usage are likely to provide an underestimate of AI's ongoing impact on firms; whether businesses adopt AI directly or not, many of the products and services they purchase and use implement AI. For example, online advertising platforms, navigation systems, and recommendation systems all commonly implement AI and have been widely adopted.

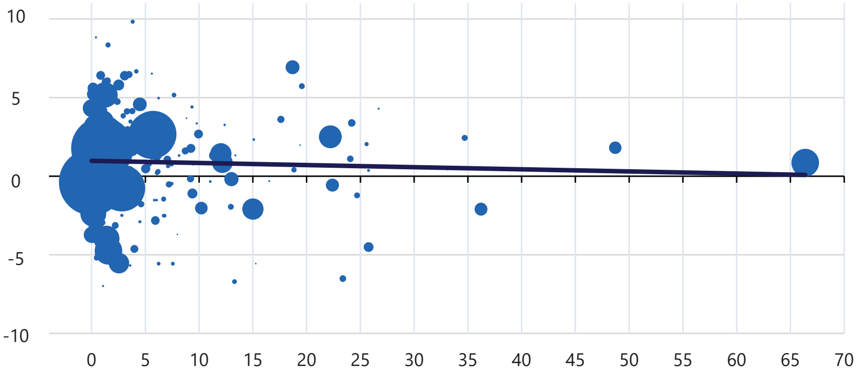
Limited evidence also suggests AI's impact on labor market decision-making. For example, commuting zones with greater industrial robot adoption in the 1990s and 2000s saw reduced employment and wage growth, and these effects can be distinguished from the simultaneous impact of import competition (Acemoglu and Restrepo 2020). Though robots are only one form of automation, and not all robots use AI extensively, predicting a robot's surroundings and interactions with others is often critical to its use. Businesses with task structures exposed to AI showed a rapid increase in AI-related job vacancy postings through the 2010s, but they simultaneously reduced hiring of non-AI-related positions, which could indicate the substitution of AI for human labor (Acemoglu et al. 2020). Evidence from Dutch employers suggests that workers whose jobs are displaced by automation are less likely to be working and more likely to retire than their peers (Bessen et al. 2023). Collectively, these papers suggest that a mix of complementarity to and substitution from AI is likely already happening.

Using the occupation-level exposure measure discussed earlier in this chapter, the CEA is also able to identify what percentage of workers in each industry are most likely to be exposed to AI, and whether these workers have high or low performance requirements that could be associated with complementarity or substitution. The two panels of figure 7-9 plot these measures against recent changes in employment growth relative to the long

Figure 7-9. Industry AI Exposure versus Payroll Employment Growth Relative to Long-Run Trends

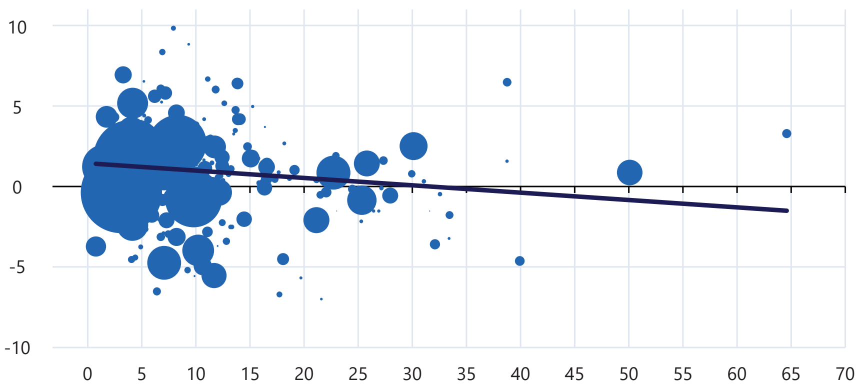
A. AI-Exposed Employment with High Performance Requirements

Difference in growth rate of payroll employment from 2023 to annualized rate between 2007 and 2019 (percentage points)



B. AI-Exposed Employment with Low Performance Requirements

Difference in growth rate of payroll employment from 2023 to annualized rate between 2007 and 2019 (percentage points)



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Sources: Bureau of Labor Statistics (Occupational Employment and Wage Statistics); Pew Research Center; CEA calculations.
Note: Occupations are matched to the most detailed industry data available in the Current Employment Statistics. Point sizes are proportional to industry employment and linear predictions are weighted by industry employment. These outliers are not shown: 213, support activities for mining; 313, textile mills; 3132, fabric mills; 3361, motor vehicle manufacturing; and 3212, veneer, plywood and engineered wood product manufacturing.
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run trend from 2007 to 2019. The figure demonstrates three things: (1) most industries and most workers still have relatively low exposure; (2) employment in AI-exposed occupations is dispersed across industries, with only a handful of small industries having most of their employment in highly exposed occupations; and (3) relatively little evidence of heterogeneity by performance requirements has emerged. In particular, the similarity of the relationship plotted in the two panels suggests that neither large-scale complementarity to nor substitution from AI is taking place. Industries with a high share of exposed employment saw slightly less rapid employment growth in 2023 relative to long-run patterns, but thus far AI exposure has little explanatory power.

Preparing Institutions for AI

Productivity gains make society richer by allowing it to do more with fewer resources. The new economic activity permitted by AI can, in principle, provide the potential for everyone to be better off than they were before. However, a world where AI increases everyone's living standards is not guaranteed. Institutions and regulatory environments have important effects on the ways that technologies are developed and deployed, and on how their effects are felt. Just as strong but flexible institutions were necessary for the Industrial Revolution (e.g., Mokyr 2008), and as poor institutions still limit development in much of the world (e.g., Acemoglu, Johnson, and Robinson 2005), so too will details of the U.S. institutional environment dictate both how widely AI is adopted and who benefits from it.

The Federal Government's role goes beyond ensuring that the gains brought about by AI are widely shared. It must also ensure that the costs to harmed individuals are addressed. To the extent that AI may displace some employees, evidence shows that workers are likely to experience significant negative effects. These effects may be sizable even if the labor market remains strong and despite the fact that most workers eventually find new jobs (Davis and von Wachter 2011). However, AI's potential harm is broader than its impact on affected workers. Loss of consumer privacy, reduced market competition, and increased inequality are all potential consequences of AI that the government can help manage (e.g., Acemoglu 2021). The potential use of AI by malicious actors is also a concern—and one reason the Biden-Harris Administration has begun taking specific steps to develop best practices and secure the nation's infrastructure (White House 2023a).

Many new technologies affect only a single market or a few products. AI has applications touching most industries and markets, likely including some that do not yet exist. Also, the inputs to many AI models include data generated from vast swaths of economic activity. Outlining every way in which the institutional environment affects AI is therefore impossible. Still, it is worth considering the broad economic forces at issue and some of the ways the economy's institutions must be reexamined to ensure they can manage an economy in which AI is a fundamental feature.

Ownership, Liability, and Regulation

The usefulness of AI arises from its ability to make predictions, automate tasks, or generate outputs that humans value. However, these same characteristics that make AI systems useful often raise important questions about both intellectual property rights and liability. This has been true of AI systems in the past, and the rapid rise of generative AI systems has expanded the scope of issues. For example, a number of recent copyright infringement lawsuits have challenged AI companies' argument that generative AI systems can be trained on copyrighted materials under fair use provisions (Appel, Neelbauer, and Schweidel 2023; CRS 2023a; Sag 2023; Setty 2023; Oremus and Izadi 2024). Similarly, creators have contested the training of AI systems on their creative works, and celebrities have contested the use of AI to replicate their likenesses from their personal traits (Kadrey et al. v. Meta Platforms 2023; Horton 2023; Kahveci 2023). Furthermore, scholars have begun to weigh numerous AI-related challenges to the boundaries of liability law, such as generative AI systems that could produce defamatory speech, self-driving cars that could harm pedestrians, or AI systems that could be used to commit crimes (Brown 2023; Gless, Silverman, and Weigend 2016; King et al. 2020). The way these issues are resolved will alter incentives for content creators, platforms, and end users. Thus, the decisions that regulators and the legal system make will be a critical element in determining whether and how AI is adopted and deployed (e.g., Brodsky 2016; Sobel 2017), and may have an impact on competition as well (e.g., Tirole 2023; Volokh 2023). An economic framing of ownership and liability provides key insights for regulators in adapting to the challenges presented by AI.

In a strict legal sense, ownership of AI inputs and systems is generally not in question.[28] However, the contemporary economic conception of ownership is considerably broader. Rather than focusing on the absolute rights of owners to possess an asset themselves, economists emphasize that the value of ownership derives from the capabilities it provides: the ability to select the use of an asset, to prohibit its use by others, and to form contracts around this use (e.g., Alchian 1965; Barzel and Allen 2023).[29] Regulations and legal constraints place limits on ownership, either by limiting what owners can do or by limiting what owners can prevent others from doing. For the

[28] Regarding AI outputs, courts have considered cases in which an individual applied for patent or copyright protections for AI outputs, and have generally ruled that such ownership rights are not available to outputs generated by AI without human involvement (e.g., *Thaler v. Vidal* 2022; *Thaler v. Perlmutter* 2023).

[29] Extensive legal scholarship has also considered the nature of ownership, and is characterized by multiple competing approaches. Economic thought has played a role in outlining the benefits and drawbacks to each approach, although many economically salient features of ownership are not strictly dependent on the legal theory applied (e.g., Coase 1960; Honoré 1961; Bell and Parchomovsky 2005; Merrill and Smith 2011; Smith 2012; and Medema 2020).

same reason, ownership rights and liability assignments are only economically meaningful to the extent that they can be enforced (e.g., Calabresi and Melamed 1972).

The incentives created by ownership rights have very broad economic effects. For example, the incentives of ownership are fundamental to determining how and why firms form, and to how product markets and financial markets are structured (e.g., Grossman and Hart 1986; Aghion and Bolton 1992). Similarly, the ability to profit from new technologies is critical not only for their development but also for economic growth as a whole (e.g., Aghion and Howitt 1992). Even in cases where strict legal ownership is not in question, regulatory choices that change the incentives around ownership may have sizable effects on overall market competition, as well as on the path of technology development itself. With AI in particular, the incentives of ownership will shape developers' decisions to invest in advancing AI's technological frontier, companies' decisions to deploy or commercialize AI applications, and many other consequential decisions.

A particularly economically important capability of owners is that they can form contracts related to the assets they own. Through these contracts, the owners of assets can assign many or most of their specific rights and responsibilities to others to reduce economic inefficiencies. Consider, for example, an out-of-town landlord who contracts with a local management company to find tenants and fix things that break. In some cases, clear assignment of property rights and contracts are sufficient for markets to achieve economic efficiency (Coase 1960). However, transaction costs, uncertainty, private information, and other common features of the economy can cause contract mechanisms to break down (e.g., Medema 2020). Writing contracts that efficiently address all situations may be too costly to be practicable. Moreover, unexpected or unplanned situations may also arise for which writing contracts is impossible. Because the owner remains the residual claimant (Fama and Jensen 1983), they bear both the positive and negative consequences that may result. In these circumstances, contracts are said to be incomplete, and market mechanisms may fail to achieve efficient outcomes. Owners adapt to some market failures by forming firms, or by merging or otherwise integrating to mitigate the problem (Williamson 1971; Grossman and Hart 1986). Integrations can be beneficial when they address market failures, but they also have the potential to undermine competition (e.g., Broussard 2009). In many other cases, only government regulations are capable of alleviating market failures.

The potential for incomplete contracts and associated issues related to AI is high, for several reasons. First, the technology is developing rapidly. Many specific ways in which AI will be used are still uncertain, as are the consequences of those uses. Moreover, many of the most useful AI applications must make predictions in novel environments with limited relevant training data. In such situations, even thoughtfully developed AI models are prone to unanticipated behavior. The existence of this possibility can cause potentially serious market failures (Hart 2009). Second, data inputs often originate from user activity, so negotiating directly with each user could lead to high transaction costs. A similar concern exists regarding AI models that are trained on copyrighted works from many different authors (e.g., Samuelson 2023). Also, AI providers often have considerable private information about how their models operate, which can be used to tilt contracts away from economic efficiency and in providers' favor and can prevent agreements from being reached at all (Kennan and Wilson 1993; McKelvey and Page 1999). For these and other reasons, the markets for AI technology are especially susceptible to failure, so laws or regulations that address those failures are needed to strike an economically efficient balance between AI's benefits and costs.

A related incomplete contracts issue arises because AI-created work may not be subject to copyright or other intellectual property protection (e.g., *Thaler v. Vidal* 2022; *Thaler v. Perlmutter* 2023). Intellectual property rights narrow the residual, and the lack of such rights means that restrictions on the use of AI outputs will be largely driven by contract law. When laws do not otherwise assign ownership of an asset, then the government becomes the de facto residual claimant, setting rules that manage its use and bearing responsibility for the consequences. Efficient management of common assets is often possible, although it poses unique challenges (Ostrom 1990; Frischmann, Marciano, and Ramello 2019).

Another way in which laws and regulations create incentives is through the assignment of liability. Often, liability is determined separately from ownership. However, the two concepts are linked because ownership often conveys some forms of liability, because liability is commonly transferred or constrained through contracts, and because the economic incentives of liability assignments depend on their ability to be enforced. A lengthy literature in law and economics considers the economic foundations of liability law (Calabresi 2008; Landes and Posner 1987; Shavell 2004). Major concepts from this literature—such as the economic benefit of assigning liability to the "cheapest cost avoider" to disincentivize harm efficiently—have proven influential in recent legal decisions related to digital technologies (e.g., Sharkey 2022).

When laws and regulations have an impact on ownership rights or potential liability, they often strike a delicate balance between multiple incentives. For example, when patent laws assign ownership rights, they balance the incentive to create and benefit from one's creation against the incentive to adopt and benefit from previous creations (Scotchmer 1991). Other intellectual property laws, like copyright and trademark laws, balance similar incentives. And libel laws balance the potential benefits of information dissemination against the costs of harmful misinformation (Dalvi and Refalo 2008). As technology evolves, the nature of these incentive forces can change as well, so regulations may need to be updated to establish a new balance.

Interpretations of laws have adapted substantially to accommodate the extensive technological changes of the past. For example, interpretations of the "fair use" doctrine in copyright law have depended on the technology available at the time; in recent decades, this doctrine has been interpreted to look at how transformative the new use is in order to accommodate new technologies like Internet search (Gordon 1982; Netanel 2011; Authors Guild v. Google 2015). Similarly, the interpretation of tort law has evolved repeatedly to accommodate technological changes, such as the rise of mechanized transportation and factory production (Gifford 2018). Although such adaptations may be encouraging, the ways in which existing laws and regulations can be adapted to AI is, in many cases, still an open question.

Even in cases where existing laws or regulations can adapt, there may also be other economic benefits from a proactive approach. For example, defining explicit liability rules before the situation arises can improve economic efficiency by reducing uncertainty about how liability will be assigned, narrowing the residual and creating incentives as it does so. One such case may be the liability issues related to autonomous AI systems whose actions unexpectedly harm someone (e.g., Gifford 2018; Diamantis, Cochran, and Dam 2023). Likewise, enacting more specific regulations about AI liability may also reduce the costliness of enforcement, which can improve economic incentives (Mookherjee and Png 1992). Other regulations, such as regulations that encourage increased transparency in AI systems, could also ease enforcement of liability law and improve incentives (e.g., Llorca et al. 2023).

Scholars have already identified a few specific policies as potential targets for reform. For example, in recent years some researchers have suggested adjusting or limiting patent protection to incentivize innovation more effectively (Boldrin and Levine 2013; Bloom, Van Reenen, and Williams 2019). Others have argued that the inability to patent AI-generated inventions will weaken innovation incentives (e.g., Dornis 2020). Recent empirical evidence has generally found that patenting does encourage start-up success and later innovation, but not necessarily in all markets (Gaulé 2018; Farre-Mensa, Hegde, and Ljungqvist 2019; Sampat and Williams 2019). This suggests that the limits to patentability associated with AI could be a substantial concern for innovation in some fields. Conversely, there is less evidence of a problem with AI innovation itself. Although thousands of AI-related patents are filed each year (Miric, Jia, and Huang 2022), private companies have released the algorithms used by multiple popular large-language-model AI frameworks as freely distributed open source software.

The companies' competitive strategies are often multifaceted, but they frequently appear to rely more heavily on their access to data, their ability to integrate AI into other products, or positive network effects from adoption than on the exclusive rights patent protection can provide (Heaven 2023; Boudreau, Jeppesen, and Miric 2022).

Additionally, existing regulation of Internet activity delineates between the creators of content and the platforms and providers who serve that content to consumers. Under current law, providers are shielded from liability in most circumstances for content they serve but do not create, while they are also given latitude to moderate the content (e.g., CRS 2024). Online generative AI services blur the conceptual distinctions underpinning this law. When a generative AI summarizes an article and posts it online instead of a human, is the AI a content creator? If so, are AI algorithm operators themselves liable for harm like defamation that may originate in the initial article? Holding operators liable for such uses of their technology could greatly limit generative AI adoption, even in places where it is beneficial (Perault 2023). Conversely, the link between AI data inputs and outputs is often opaque; in such situations, if AI systems operators are not held liable, then enforcement of liability against other parties may be impracticable (Bambauer and Surdeanu 2023).

In summary, many of AI's most profound potential effects are closely linked to the ways in which it tests existing delineations of ownership rights and liability. Economics has a long history of demonstrating just how important those choices about ownership rights and liability can be. As policymakers and courts consider their options for addressing AI-related issues, they will benefit from taking these economic forces into account.

Competition and Market Structure

Competition creates incentives that increase economic welfare and, as President Biden has stressed, lower costs. It pushes firms to lower prices, raise wages, and create higher-quality products (the combination of lower prices and higher wages suggests that competition can reduce economic rents that occur amid insufficient competition). And although its relationship with innovation is complicated, competition generally encourages innovation at the technological frontier (Aghion et al. 2005; Bloom, Van Reenen, and Williams 2019). In markets without robust competition, firms have the ability to increase their own profits or advance their other interests at the expense of others by raising prices, reducing production, or strategically underinvesting in quality, customer service, or innovation. Because lower competition is typically associated with higher profits, firms may be incentivized to merge, to foreclose rivals, or to take other actions in order to undermine competition. Mergers and some types of conduct that reduce competition are illegal under antitrust laws, but the government also shapes markets and influences competition through regulation and its own conduct as a market participant.

As last year's *Economic Report of the President* discussed, the economics of competition are particularly complex in digital markets (CEA 2023). AI is widely used in many of these digital markets, including to set prices in platform markets, to optimize content on social media, and to optimize inventory levels. However, because of their widespread and growing adoption, AI systems are also present in many markets outside digital platforms.

In all these cases, the addition of AI can have positive or negative effects on competition. In many cases, it can create better products and lower costs. In some cases, the adoption of AI systems can also increase competition by making it easier for new firms to enter or by lowering switching costs. For example, AI-powered machine translation can reduce language barriers, allowing greater international competition (Brynjolfsson, Hui, and Liu 2019). Similarly, AI can alleviate other barriers by making it easier to convert computer code from one language to another, or enter into software development (e.g., Roziere et al. 2020; Weisz et al. 2022; Peng et al. 2023). Conversely, AI integrations might inappropriately reduce competition by increasing the barriers to switching providers and thus locking in customers who use their services. Data or integration methods locked to proprietary AI models, for example, can create such barriers.

AI can also be used as a tool for either tacit or explicit collusion that can harm competition. AI systems may make it less costly for firms to closely track and respond to the behavior of rivals or facilitate sharing competitively sensitive information to which competing firms otherwise would not be privy, factors that make it easier to sustain collusion (Tirole 1988). They may also make it simpler for firms to engage in complex multimarket interactions that also can facilitate collusion (Bernheim and Whinston 1990). Recent research suggests that these pricing algorithms may actually learn collusion as the optimal outcome of their profit-maximizing algorithm (Calvano et al. 2020; Johnson and Sokol 2020; Abada and Lambin 2023).

"Learning by doing" is an economically important process in many markets (e.g., Arrow 1962; Thompson 2010), and it has particularly important implications for competition in many AI markets. On one hand, such learning improves the product, creating positive network effects that can, in turn, attract more users and lead to a virtuous cycle that benefits consumers (Gregory et al. 2021). On the other hand, the same network effects that can create product improvements can also drive smaller firms out of the market, leaving a market with only a handful of dominant players. And, in the long run, such network effects may also dampen future innovation and competition by raising barriers to entry. Even entrants that have better or more efficient underlying technology may struggle to attract users if they lack the data to appropriately tailor their products (Werden 2001; Farrell and Klemperer 2007). Finally, some AI systems automate feedback loops to continuously improve, in effect automating the learning-by-doing process. Such automation likely strengthens network effects, in turn increasing potential consequences, both positive and negative.

In addition to AI's effects on other markets, competition between AI providers will be important for AI's deployment and ultimate impact. In some markets, entry costs are relatively modest, data are widely available, and network effects are not too strong. In such markets, competition may be robust and involve many small providers. Similarly, some AI systems will be developed internally by firms that do not specialize in the technology, but who use it to support their overall business. Multitiered integrations are also likely, such as for systems in which general-purpose models interface with other, more specialized add-on tools.[30] In other cases, however, some combination of high entry costs, data availability, and network effects may drive markets toward having only a small number of players. Markets for generative AI products, which require huge amounts of data and computing power to train, may be particularly prone to this issue, with some even suggesting that such markets may naturally trend toward monopoly (Narechania 2022). There is an inherent economic trade-off between the cost of entry and the benefits of increased competition, but appropriate government policy can help ensure that a monopoly outcome is not a foregone conclusion.

Competition inside a market is also affected by competition in adjacent markets. For example, even if there are many aluminum can suppliers, competition may be weak if there is only one supplier of the aluminum itself. In this way, supply chains are only as competitive as their least competitive link, a so-called competitive bottleneck. Firms may also participate in multiple markets through vertical integration or exclusive contracting. In such situations, firms may use a dominant position in one market to undermine competition in another (Ordover, Saloner, and Salop 1990; Moresi and Schwartz 2021). Furthermore, self-preferencing by vertically integrated firms can result in inferior technologies being adopted even in the long run (Katz and Shapiro 1986).

Scholars have suggested that all these concerns may be particularly acute in digital platforms and AI markets (Athey and Scott Morton 2022; Vipra and Korinek 2023). For example, many AI-related products have been built by organizations with ties to existing large technology firms that themselves are increasingly vertically integrated across the AI stack. Similarly, some inputs necessary to create AI systems are controlled by a small number

[30] For example, several foundation model providers have released libraries that allow their services to be easily integrated into other software, including other AI models (e.g., Anthropic 2024; OpenAI 2024).

of companies, raising concerns about the potential for competitive bottlenecks. For example, the design, production, and equipment used to produce the specialty chips needed to power AI computing are each controlled by a handful of firms, as is the provision of cloud computing (Narechania and Sitaraman 2023).

AI policy will have a large role in ensuring healthy and competitive markets, protecting consumers of AI outputs, workers who use AI systems, and other market participants. Competition-aware policy can avoid inadvertently increasing barriers to entry while ensuring that some providers are not unduly favored over others. Antitrust enforcement will play a critical role, but so too will other government policies.

Broadly, ex ante regulation or other policies can improve efficiency relative to ex post antitrust enforcement by offering certainty to businesses and avoiding costly ex-post remedies (Ottaviani and Wickelgren 2011). At the same time, such ex ante policies could backfire if poorly conceived or executed. Developing standards in an open and transparent manner can avoid inadvertently favoring a market's incumbents or making it difficult for smaller firms to comply or enter.

Similarly, freely available and portable data may encourage a competitive landscape and ensure that gains from data are widely distributed. Market participants often have an incentive to maintain proprietary data. Data can be copied at low cost, and productive improvements from data may be easily replicated, so firms are likely to compete away gains from publicly available sources. However, reliance on proprietary data could cause fragmented AI markets to emerge. If each firm can access only a small portion of the available data, AI systems may not function as well as they otherwise could. This has been an ongoing problem in pharmaceutical research (Schneider et al. 2020) and is increasingly an issue on the Internet, where content and user data are often locked into proprietary tools and applications. Increased availability of public data, such as that produced by the Federal Government, may encourage more competition. Restrictions on what data may remain proprietary and appropriate regulations on how AI companies can use the data collected from their users may do the same.

Additionally, policies that encourage portability and interoperability can reduce barriers to competition (Brown 2020). Market providers generally have an incentive to reduce customer switching, and systems that encourage locking in may be developed to gain an anticompetitive advantage. Interoperability requirements make switching providers easier, reducing firms' ability to gain an advantage through lock-in. In labor markets, firm strategies—such as noncompete agreements, training repayment agreements, and other methods—can tie workers to specific firms; however, these tactics could also limit competition in markets for AI skills. The sophisticated skills needed to develop and work with AI systems can only be put to best use throughout the economy if workers can transition freely in competitive labor markets, and so policies that reduce labor market barriers could improve competition in markets for AI itself.

Finally, sharing competitively sensitive information through AI systems can undermine competition and pose risks to firms under existing antitrust laws. Government efforts to educate firms about these risks and to promote sound antitrust compliance policies can reduce the possibility that AI technologies will be used to lessen competition.

In summary, the policies needed to encourage competition go well beyond the traditional tools of merger or monopolization analysis. Competition will be affected by the choices the Federal Government makes to regulate AI and its markets. The correct approach requires consideration of the sophisticated ways in which individual markets interact with the technological landscape and learning lessons from past instances in which new technologies were not regulated to promote competition at the outset. The Biden-Harris Administration has released new competition guidance encouraging the Federal Government's agencies to consider these issues in their analyses of regulations (OMB 2023a), and the Office of Management and Budget (OMB 2023b) has encouraged agencies to consider competition in their use and procurement of AI tools. This holistic framing may be particularly important as the role of AI in the economy grows. (See box 7-3.)

Labor Market Institutions

AI has real potential to transform the labor market. The empirical case for permanent market displacement is limited, but the transition to an economy that thoroughly incorporates AI could displace many workers from their existing jobs, create many new types of jobs, and affect the work of others dramatically. What labor market features will be most important to protecting workers in the transition, and what features will help ensure they are prepared to use AI?

In part, policies that reduce AI's disruptive effects on labor markets are the same ones that encourage efficient and responsible AI investment. Encouraging innovation, reducing regulatory uncertainty, and supporting needed human capital investment are all important goals of AI policy. Responsible stewardship of the economy as a whole is also important, as the negative effects on workers of job displacement are considerably magnified by weak economic conditions (Davis and von Wachter 2011).

In practice, the negative effects of technological and regulatory change are often quite concentrated on specific industries, occupations, and geographic regions. The experience of trade liberalization has shown that negative effects of job displacement can persist for many years and spill over to local economies (Autor, Dorn, and Hanson 2013, 2021). Many policy

Box 7-3. What Can Voluntary AI Agreements Accomplish?

The Biden-Harris Administration announced voluntary agreements covering cybersecurity, algorithmic discrimination, output watermarking, and other issues with seven leading artificial intelligence companies in July 2023; the agreement now covers fifteen companies (White House 2023b). The agreements were a step toward creating the first AI-specific guidelines and guardrails at a critical time. They demonstrated not only the industry participants' interest and willingness to work toward the common good, but also their belief that it is possible to make progress through open dialogue, unilateral action, and social norms. Still, the agreements are unlikely to be a long-term solution.

Meaningful voluntary commitments are rare in the private sector. If taking an action is in a firm's unilateral interest, no commitment is necessary. If the action is not in the firm's unilateral best interest, the company will have an incentive to avoid making such a commitment.

The features that make agreements meaningful can also provide the incentive to change course later. For example, the existence of a voluntary agreement can create opportunities for new entrants. These new firms may decline to make the commitment and may use that flexibility to outcompete committed firms (Brau and Carraro 1999). Existing firms may respond to competition by dropping out of an agreement or abandoning its limiting principles.

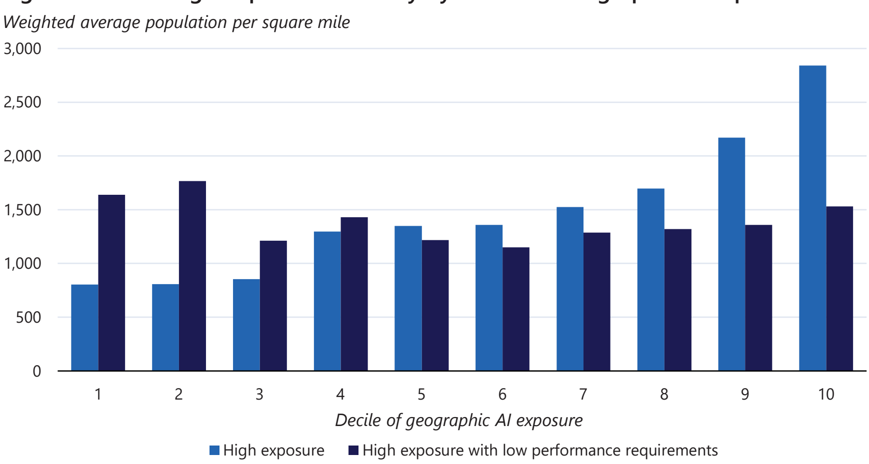
The recent voluntary agreement covers major players in generative AI. These markets feature many barriers to entry (Federal Trade Commission 2023), making them a relatively favorable environment for voluntary agreements to form and be sustained. Other AI market segments that lack similar barriers may be less amenable to voluntary cooperation.

options for addressing AI substitution are similar to those suggested in the context of past economic shocks.

Recent trade shocks have predominantly affected people in areas that became subject to new import competition. Analogously, AI's effects are likely to be felt most acutely in places where AI-exposed workers live. The CEA has mapped its occupation-level measure of AI exposure to workers' places of residence, showing where exposure is most likely to have localized effects. As figure 7-10 indicates, in the most AI-exposed regions, the average worker's neighborhood is more than three times as dense as it is in the least exposed regions. However, the story is somewhat different for workers whose jobs have low performance requirements. Both the most exposed and least exposed areas to this type of work are relatively dense, and less dense areas are often in the middle of the exposure distribution.

The evidence suggests that AI's effects are likely to be felt most strongly in urban areas. This finding is consistent with other recent research demonstrating that a preponderance of innovation, along with a large fraction of new work, occurs in cities (Lin 2011; Gruber, Johnson, and Moretti 2023). Conversely, to the extent that exposure with a low average level of required activity performance captures the possibility of job substitution, the evidence suggests that only a subset of urban areas may experience negative effects from widespread job displacement. Prior research suggests one likely reason for the pattern: Occupational segregation is high, and overall economic residential segregation has increased over time (Florida and Mellander 2015; Bischoff and Reardon 2013). While some workers in urban areas may become more productive as a result of AI, others could be displaced, and the two sets of workers may live in different neighborhoods, with differing implications for policy. And although greater job access in dense urban labor markets may make it relatively easy for workers to weather economic disruptions, evidence also suggests that at the local level, the effect of competing with many displaced individuals can outweigh the effect of increased nearby opportunities (Haller and Heuermann 2020). In short, although evidence about geographically concentrated AI exposure is limited, there is reason to believe that targeted place-based policies could play a useful role, much as they play a role in other contexts such as clean energy transitions (CEA 2022).

Figure 7-10. Average Population Density by Decile of Geographic AI Exposure



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Sources: American Community Survey; Department of Labor; Pew Research Center; CEA calculations.

Note: Average density is the population-weighted geometric mean density of each workers' census tract of residence. Geographic units are public-use microdata areas. Average population per square mile is the population-weighted geometric mean density of Census tracts in each unit. Analysis uses full-time, full-year workers age 16 plus. Performance requirements are captured using the O*NET data measuring degree of difficulty or complexity at which a high AI-exposed work activity is performed within an occupation. Low indicates an average degree of difficulty below the median.

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Individual firms will play a major role in training their employees to work with AI, particularly in cases where firms use customized systems or adopt foundation models in unique ways. However, government can help ensure that the training benefits workers. Economists distinguish general human capital, which can be put to broad productive use, and firm-specific human capital, which is not portable. Because many AI models are purpose-built for a particular firm's needs, many of the skills workers need to use the models will likely be firm-specific or learned on the job. Economic theory has shown that firm-specific human capital gives employers labor market power over their employees and can allow them to keep wages low (Acemoglu and Pischke 1998). In contrast, because general human capital is portable, it gives employers no additional market power, and firms have a lower incentive to invest in it.

The Biden-Harris Administration has made record investments to encourage general human capital training through registered apprenticeships—and recently proposed to further expand and modernize the National Apprenticeship System (White House 2023c; DOL 2023b). Registered apprenticeships provide firms with resources to invest in workers' skills and provide opportunities for workers to learn on the job with a mentor while getting paid. They also establish standards to ensure the resulting human capital is portable and of high quality. Firms propose and register an apprenticeship program in an approved occupation; the set of apprenticeable occupations already includes many that are likely to work with AI technologies. Through increased flexibility, improved processes, and better data collection, the proposed improvements to the Registered Apprenticeship System would help to ensure that workers can develop the skills they need to work with AI.

Unions can also help develop workers' skills and protect their livelihoods. Unions counteract the effects of employers' labor market power and have been shown to yield increased worker training (Booth and Chatterji 1998; Green, Machin, and Wilkinson 1999). More generally, giving workers a voice in how AI is used may help ensure that they benefit from its use. Collective bargaining has empowered workers to secure protections related to the use of AI, such as the protections for screenwriters and actors secured in their respective union contracts (WGAW 2023; SAG-AFTRA 2023). The engagement of frontline workers on the development of AI could also have beneficial effects on the successful deployment of these systems (Kochan et al. 2023). Unions can also have many other economic effects, including positive effects on compensation for workers, as well as effects on firm incentives to substitute capital for labor and to engage in research and development (e.g., Hirsch 2004; Knepper 2020; U.S. Department of the Treasury 2023). The net effect of these incentives on AI adoption is unclear and is likely to depend on the particular structure of unionized industries (Haucap and Wey 2004).

The Federal Government can help ensure workers displaced by AI are prepared to take their next steps in the economy both indirectly and directly through Federal investment and programs. One critical indirect mechanism that exists to ensure smooth labor transitions is the unemployment insurance program. Unemployment insurance keeps workers economically stable, and it encourages them to find new employment rather than leave the labor force. Finding new, high-quality jobs for displaced workers may take time, and a flexible unemployment insurance system allows workers to search for higher-paying and better jobs (Chetty 2008; Schmieder, von Wachter, and Bender 2012; Nekoei and Weber 2017).

The government can also help workers transition to new careers directly by combining unemployment insurance with explicit training and reemployment services. This approach is currently embodied by the Reemployment Services and Eligibility Assessment Grants program (DOL 2023c). It has also been used to assist workers losing their jobs to foreign competition via the Trade Adjustment Assistance (TAA) Program, which has expired for new beneficiaries.[31] Recent research using worker-level administrative data suggests that displaced workers who are approved for TAA increase their cumulative earnings by tens of thousands of dollars in the years following the program (Hyman 2022). This research also finds suggestive evidence that the skills learned from TAA may depreciate over time, an area of concern as AI technology rapidly evolves. Policymakers could build upon lessons learned from TAA to revitalize and expand a program for displaced workers that accommodates AI-related displacement as a way to ensure that workers remain in the labor force and are able to work productively with AI. (See box 7-4.)

Measuring AI and Its Effects

A common thread among the various questions and policies outlined above is that they require observability. If the government cannot observe the ways and extents to which AI is being used, it may be difficult to enforce existing laws and to target and implement new regulations. Similarly, the government is constrained in its ability to assist workers who are displaced by AI if it cannot observe who these workers are. Policies that improve observability or increase data collection may have a high impact if they allow the government to identify AI adoption when it occurs, distinguish AI-generated outputs from human-generated ones, and measure more precisely the economic effects of AI.

[31] See CRS (2023b). The TAA program's termination provisions took effect in July 2022 after Congress declined to renew funding for the program.

Box 7-4. Should AI Be Taxed?

Artificial intelligence has the capacity to increase productivity, but it may do so while displacing many workers from their current jobs or exacerbating inequality. Technology industry leaders, the European Parliament, and others have therefore suggested taxing the use of AI and related technologies. They argue that an AI tax could fund training for displaced workers and potentially reduce overall inequality (Quartz 2017; European Parliament Committee on Legal Affairs 2017; Abbott and Bogenschneider 2018).

Economists generally consider the proposed AI tax analogously to other taxes on capital as a production factor. Because some capital is durable, deciding whether to invest in it may impact productivity and growth in the future. Correspondingly, a tax that disincentivizes capital investment has the potential to be especially costly. The concern is especially salient for general purpose technologies like AI, as one of their functions is to increase existing capital's reusability (Aghion, Howitt, and Violante 2002). A lengthy literature has considered the optimal rate of capital taxation for balancing economic growth against other features of the economy and of existing tax policy (e.g., Diamond and Saez 2011; Saez and Stantcheva 2018). Rich frameworks that incorporate borrowing constraints, uncertainty, and other real-world features typically find that the optimal way to fund fiscal policy is through a mix of taxes, including on capital.

Economists have recently considered how an additional tax on AI adoption could affect both impacted workers and overall economic well-being. The effective U.S. capital taxation rate has declined in recent years, which some have argued could encourage excessive negative employment impacts through automation (Acemoglu, Manera, and Restrepo 2020). However, these researchers also argue that setting appropriate capital and labor tax rates may sufficiently ensure that excessive automation does not occur, as increased AI-specific tax rates only serve a purpose if it is infeasible to alter these broader capital tax rates. Other recent research considers technology's declining cost trend and its differential effect on present versus future workers. These papers find that taxing AI in excess of other capital can be beneficial in the short run but not in the long run (Guerreiro, Rebelo, and Teles 2022; Thuemmel 2022).

How might taxation affect AI-related innovation itself? Evidence from historical patent data suggests that inventors respond to taxation-based incentives, both in how much they innovate and in where they do so (Akcigit et al. 2021). Software-related patents, including for AI technology, comprise roughly half of those issued today, and this patenting activity is particularly geographically clustered (Chattergoon and Kerr 2021). Taxes on AI adoption and innovation may therefore have implications for overall growth, place-based policies, and other initiatives.

Observing AI adoption and measuring its effects is inherently challenging. This is in part because firms that adopt AI do so in many ways. They may have service contracts with large technology providers, make use of purchased or open source tools with proprietary data, engage in in-house model development, or purchase inputs for which AI is only one component. AI models may be large, in the sense of containing many parameters and being trained on large volumes of data, or they may be small. And, the potential negative effects of AI may be closely linked to the model's actions, or they may be further afield in upstream or downstream markets. Nonetheless, the Federal Government is taking and has taken steps to improve observability of AI adoption.

To address certain risks to safety and security, the recent Executive Order identifies reporting thresholds for very large AI models based on the number of arithmetic operations used to train them (White House 2023a). These thresholds may be well suited to identify providers in certain segments of the AI market in the future, such as large language models. Identifying such providers may be sufficient to identify and address some kinds of AI-related risks. At the same time, substantively all effects from AI adoption so far—including negative effects, such as discrimination—have been associated with models that did not meet these thresholds (e.g., Brown et al. 2020). More generally, in many economic contexts, there is little reason to believe that the potential for negative effects from an AI model is proportional to its underlying scale. So, although arithmetic reporting thresholds have value, and additional thresholds could be implemented in the future, other approaches are also necessary to address the wide range of AI-related risks.

The Executive Order also directs agencies to consider methods of identifying AI-generated outputs such as watermarking and content detection. These approaches could help observe and measure some types of AI usage. If watermarking requirements are sufficient to identify the origins of an AI output, then harmful outputs can also be traced back to their creators. However, the practical uses of watermarking are likely limited to generative AI outputs that are widely distributed. Many other uses of AI in economic activity are not directly observable outside the firms where they occur. Also, enforcement of watermarking requirements may be difficult unless the generative AI models used to produce these outputs have already been identified, or an alternative method of content detection is successfully implemented.

A complementary approach may be to identify the workers and other parties who are most likely to be affected by AI. Surveys of firms already collect some information about AI adoption (Zolas et al. 2020), and data from administrative processes are used to produce many other economic statistics that could be useful. However, current gaps in data collection significantly limit some uses of these data. For example, occupation is a key dimension along which exposure to AI is likely to have a labor market impact, so policies that target vulnerable or displaced workers based on their occupation could play an important role in the overall policy responses to AI.[32] However, linking workers with their occupations consistently is challenging. Surveys that include occupation are subject to substantial measurement error, and programs such as unemployment insurance often have difficulty collecting this information in a standardized way (Fisher and Houseworth 2013; DOL 2023a). Furthermore, even the best sources of administrative data on workers in the United States do not include information on their occupations. Additional administrative processes or enhanced surveys may address gaps in government data collection, making it easier to implement policies that effectively target and assist affected workers.

Conclusions and Open Questions

AI has the potential to increase economic well-being. Like many previous technologies, it will do so by transforming the economy in both expected and unexpected ways. Economic theory demonstrates that the changes have the capacity to benefit everyone, but recent empirical evidence shows that broad-based benefits are not guaranteed. Sensible policies to encourage responsible innovation, protect consumers, empower workers, encourage competition, and help affected workers adjust are critical.

Many open questions remain, and the Biden-Harris Administration is working continuously to seek answers to these questions and incorporate the lessons it learns into its regulatory and policy responses. In 2022, the White House's Office of Science and Technology Policy released its Blueprint for an AI Bill of Rights, which highlights five principles covering many of the most pressing concerns about AI (White House 2022). Agencies throughout the Federal Government are taking steps to implement the blueprint's recommendations. The National AI Advisory Committee, launched in May 2022, has engaged leaders from industry and academia to consider major policy questions and make recommendations (NAIAC 2023). The National Institute of Standards and Technology has launched the U.S. AI Safety Institute to enable collaboration on safety and security standards (NIST 2023). And the President's Executive Order 14110 has identified key government agencies and bodies to oversee and advise on numerous other AI-related issues. The order directs the identified organizations to study AI-related needs and make recommendations for additional tools required to address them (White House 2023a).

[32] For example, policies that target specific occupations could in many cases reduce the administrative burden and practical difficulty of demonstrating displacement.

The future path of technological change is always uncertain, but the Biden-Harris Administration is working to ensure that the Nation's institutions and policies are prepared for the changes that AI will bring. As AI's role in the economy grows, the Federal Government will need to continually evaluate its institutional framework. Only by thinking broadly about AI and its effects can society balance the technology's potential for harm against its many possible benefits.

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Chapter 7

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