



National  
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# THE ECONOMICS OF ARTIFICIAL INTELLIGENCE

## *An Agenda*

Edited by Ajay Agrawal,  
Joshua Gans, and Avi Goldfarb

Finding Needles in Haystacks: Artificial Inte...

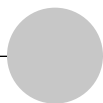
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# **The Economics of Artificial Intelligence**



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**National Bureau of  
Economic Research  
Conference Report**



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# **The Economics of Artificial Intelligence: An Agenda**

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Edited by

**Ajay Agrawal, Joshua Gans,  
and Avi Goldfarb**

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# Contents

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Acknowledgments xi

**Introduction** 1

Ajay Agrawal, Joshua Gans, and Avi Goldfarb

## I. AI AS A GPT

**1. Artificial Intelligence and the Modern  
Productivity Paradox: A Clash of  
Expectations and Statistics** 23

Erik Brynjolfsson, Daniel Rock, and  
Chad Syverson

*Comment:* Rebecca Henderson

**2. The Technological Elements of  
Artificial Intelligence** 61

Matt Taddy

**3. Prediction, Judgment, and Complexity:  
A Theory of Decision-Making and  
Artificial Intelligence** 89

Ajay Agrawal, Joshua Gans, and Avi Goldfarb

*Comment:* Andrea Prat

**4. The Impact of Artificial Intelligence  
on Innovation: An Exploratory Analysis** 115

Iain M. Cockburn, Rebecca Henderson,  
and Scott Stern

*Comment:* Matthew Mitchell



- 5. Finding Needles in Haystacks: Artificial Intelligence and Recombinant Growth** 149  
Ajay Agrawal, John McHale,  
and Alexander Oettl
- 6. Artificial Intelligence as the Next GPT:  
A Political-Economy Perspective** 175  
Manuel Trajtenberg

II. GROWTH, JOBS, AND INEQUALITY

- 7. Artificial Intelligence, Income, Employment,  
and Meaning** 189  
Betsey Stevenson
- 8. Artificial Intelligence, Automation, and Work** 197  
Daron Acemoglu and Pascual Restrepo
- 9. Artificial Intelligence and Economic Growth** 237  
Philippe Aghion, Benjamin F. Jones, and  
Charles I. Jones  
*Comment:* Patrick Francois
- 10. Artificial Intelligence and Jobs:  
The Role of Demand** 291  
James Bessen
- 11. Public Policy in an AI Economy** 309  
Austan Goolsbee
- 12. Should We Be Reassured If Automation  
in the Future Looks Like Automation  
in the Past?** 317  
Jason Furman
- 13. R&D, Structural Transformation,  
and the Distribution of Income** 329  
Jeffrey D. Sachs
- 14. Artificial Intelligence and Its Implications  
for Income Distribution and Unemployment** 349  
Anton Korinek and Joseph E. Stiglitz
- 15. Neglected Open Questions in the  
Economics of Artificial Intelligence** 391  
Tyler Cowen

### III. MACHINE LEARNING AND REGULATION

- |  |     |
|--|-----|
| <b>16. Artificial Intelligence, Economics, and Industrial Organization</b>                                       | 399 |
| Hal Varian   |     |
| <i>Comment:</i> Judith Chevalier   |     |
| <b>17. Privacy, Algorithms, and Artificial Intelligence</b>  | 423 |
| Catherine Tucker   |     |
| <b>18. Artificial Intelligence and Consumer Privacy</b>  | 439 |
| Ginger Zhe Jin   |     |
| <b>19. Artificial Intelligence and International Trade</b>   | 463 |
| Avi Goldfarb and Daniel Trefler  |     |
| <b>20. Punishing Robots: Issues in the Economics of Tort Liability and Innovation in Artificial Intelligence</b> | 493 |
| Alberto Galasso and Hong Luo   |     |

### IV. MACHINE LEARNING AND ECONOMICS

- |   |     |
|---|-----|
| <b>21. The Impact of Machine Learning on Economics</b>                                    | 507 |
| Susan Athey   |     |
| <i>Comment:</i> Mara Lederman   |     |
| <b>22. Artificial Intelligence, Labor, Productivity, and the Need for Firm-Level Data</b> | 553 |
| Manav Raj and Robert Seamans  |     |
| <b>23. How Artificial Intelligence and Machine Learning Can Impact Market Design</b>      | 567 |
| Paul R. Milgrom and Steven Tadelis  |     |
| <b>24. Artificial Intelligence and Behavioral Economics</b>                               | 587 |
| Colin F. Camerer  |     |
| <i>Comment:</i> Daniel Kahneman   |     |
| Contributors  | 611 |
| Author Index  | 615 |
| Subject Index   | 625 |



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# Finding Needles in Haystacks

## Artificial Intelligence and Recombinant Growth

Ajay Agrawal, John McHale, and Alexander Oettl

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The potential for continued economic growth comes from the vast search space that we can explore. The curse of dimensionality is, for economic purposes, a remarkable blessing. To appreciate the potential for discovery, one need only consider the possibility that an extremely small fraction of the large number of potential mixtures may be valuable. (Romer 1993, 68–69)

Deep learning is making major advances in solving problems that have resisted the best attempts of the artificial intelligence community for years. It has turned out to be very good at discovering intricate structure in high-dimensional data and is therefore applicable to many domains of science, business, and government. (LeCun, Bengio, and Hinton 2015, 436)

### 5.1 Introduction

What are the prospects for technology-driven economic growth? Technological optimists point to the ever-expanding possibilities for combin-

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ing existing knowledge into new knowledge (Romer 1990, 1993; Weitzman 1998; Arthur 2009; Brynjolfsson and McAfee 2014). The counter case put forward by technological pessimists is primarily empirical: growth at the technological frontier has been slowing down rather than speeding up (Cowen 2011; Gordon 2016). Gordon (2016, 575) highlights this slowdown for the US economy. Between 1920 and 1970, total factor productivity grew at an annual average compound rate of 1.89 percent, falling to 0.57 percent between 1970 and 1994, then rebounding to 1.03 percent during the information technology boom between 1994 and 2004, before falling again to just 0.40 percent between 2004 and 2014. Even the maintenance of this lowered growth rate has only been possible due to exponential growth in the number of research workers (Jones 1995). Bloom et al. (2017) document that the total factor productivity in knowledge production itself has been falling both in the aggregate and in key specific knowledge domains such as transistors, health care, and agriculture.

Economists have given a number of explanations for the disappointing growth performance. Cowen (2011) and Gordon (2016) point to a “fishing out” or “low-hanging fruit” effect—good ideas are simply becoming harder to find. Jones (2009) points to the headwind created by an increased “burden of knowledge.” As the technological frontier expands, it becomes harder for individual researchers to know enough to find the combinations of knowledge that produce useful new ideas. This is reflected in PhDs being awarded at older ages and a rise in team size as ever-more specialized researchers must combine their knowledge to produce breakthroughs (Agrawal, Goldfarb, and Teodoridis 2016). Other evidence points to the physical, social, and institutional constraints that limit access to knowledge, including the need to be physically close to the sources of knowledge (Jaffe, Trajtenberg, and Henderson 1993; Catalini 2017), the importance of social relationships in accessing knowledge (Mokyr 2002; Agrawal, Cockburn, and McHale 2006; Agrawal, Kapur, and McHale 2008), and the importance of institutions in facilitating—or limiting—access to knowledge (Furman and Stern 2011).

Despite the evidence of a growth slowdown, one reason to be hopeful about the future is the recent explosion in data availability under the rubric of “big data” and computer-based advances in capabilities to discover and process those data. We can view these technologies in part as “meta technologies”—technologies for the production of new knowledge. If part of the challenge is dealing with the combinatorial explosion in the potential ways that existing knowledge can be combined as the knowledge base grows, then meta technologies such as deep learning hold out the potential to partially overcome the challenges of fishing out, the rising burden of knowledge, and the social and institutional constraints on knowledge access.

Of course, meta technologies that aid in the discovery of new knowledge are nothing new. Mokyr (2002, 2017) gives numerous examples of how scientific instruments such as microscopes and x-ray crystallography significantly

aided the discovery process. Rosenberg (1998) provides an account of how technology-embodied chemical engineering altered the path of discovery in the petrochemical industry. Moreover, the use of artificial intelligence (AI) for discovery is itself not new and has underpinned fields such as cheminformatics, bioinformatics, and particle physics for decades. However, recent breakthroughs in AI such as deep learning have given a new impetus to these fields.<sup>1</sup> The convergence of graphical processing unit (GPU)-accelerated computing power, exponential growth in data availability buttressed in part by open data sources, and the rapid advance in AI-based prediction technologies is leading to breakthroughs in solving many needle-in-a-haystack problems (chapter 3, this volume). If the curse of dimensionality is both the blessing and curse of discovery, advances in AI offer renewed hope of breaking the curse while helping to deliver on the blessing.

Understanding how these technologies could affect future growth dynamics is likely to require an explicitly combinatorial framework. Weitzman's (1998) pioneering development of a recombinant growth model has unfortunately not been well incorporated into the corpus of growth theory literature. Our contribution in this chapter is thus twofold. First, we develop a relatively simple combinatorial-based knowledge production function that converges in the limit to the Romer/Jones function. The model allows for the consideration of how existing knowledge is combined to produce new knowledge and also how researchers combine to form teams. Second, while this function can be incorporated into existing growth models, the specific combinatorial foundations mean that the model provides insights into how new metatechnologies such as artificial intelligence might matter for the path of future economic growth.

The starting point for the model we develop is the Romer/Jones knowledge production function. This function—a workhorse of modern growth theory—models the output of new ideas as a Cobb-Douglas function with the existing knowledge stock and labor resources devoted to knowledge production as inputs. Implicit in the Romer/Jones formulation is that new knowledge production depends on access to the existing knowledge stock and the ability to combine distinct elements of that stock into valuable new ideas. The promise of AI as a meta technology for new idea production is that it facilitates the search over complex knowledge spaces, allowing for both improved access to relevant knowledge and improved capacity to predict the value of new combinations. It may be especially valuable where the complexity of the underlying biological or physical systems has stymied technological advance, notwithstanding the apparent promise of new fields such as biotechnology or nanotechnology. We thus develop an explicitly combinatorial-based knowledge production function. Separate parameters

1. See, for example, the recent survey of the use of deep learning in computational chemistry by Garrett Goh, Nathan Hodas, and Abhinav Vishnu (2017).



control the ease of knowledge access, the ability to search the complex space of potential combinations, and the ease of forming research teams to pool knowledge access. An attractive feature of our proposed function is that the Romer/Jones function emerges as a limiting case. By explicitly delineating the knowledge access, combinatorial and collaboration aspects of knowledge production, we hope that the model can help elucidate how AI could improve the chances of solving needle-in-a-haystack-type challenges and thus influence the path of economic growth.

Our chapter thus contributes to a recent but rapidly expanding literature on the effects of AI on economic growth. Much of the focus of this new literature is on how increased automation substitutes for labor in the production process. Building on the pioneering work of Zeira (1998), Acemoglu and Restrepo (2017) develop a model in which AI substitutes for workers in existing tasks, but also creates new tasks for workers to do. Aghion, Jones, and Jones (chapter 9, this volume) show how automation can be consistent with relatively constant factor shares when the elasticity of substitution between goods is less than one. Central to their results is Baumol's "cost disease," which posits the ultimate constraint on growth to be from goods that are essential but hard to improve rather than goods whose production benefits from AI-driven technical change. In a similar vein, Nordhaus (2015) explores the conditions under which AI would lead to an "economic singularity" and examines the empirical evidence on the elasticity of substitution on both the demand and supply sides of the economy.

Our focus is different from these papers in that instead of emphasising the potential substitution of machines for workers in existing tasks, we emphasise the importance of AI in overcoming a specific problem that impedes human researchers—finding useful combinations in complex discovery spaces. Our chapter is closest in spirit to Cockburn, Henderson, and Stern (chapter 4, this volume), which examines the implications of AI—and deep learning in particular—as a general purpose technology (GPT) for invention. We provide a suggested formalization of this key idea. Nielsen (2012) usefully illuminates the myriad ways in which "big data" and associated technologies are changing the mechanisms of discovery in science. Nielsen emphasizes the increasing importance of "collective intelligence" in formal and informal networked teams, the growth of "data-driven intelligence" that can solve problems that challenge human intelligence, and the importance of increased technology facilitating access to knowledge and data. We incorporate all of these elements into the model developed in this chapter.

The rest of the chapter is organized as follows. In the next section, we outline some examples of how advances in artificial intelligence are changing both knowledge access and the ability to combine knowledge in high-dimensional data across a number of domains. In section 5.3, we develop an explicitly combinatorial-based knowledge production function and embed it in the growth model of Jones (1995), which itself is a modification of

Romer (1990). In section 5.4, we extend the basic model to allow for knowledge production by teams. We discuss our results in section 5.5 and conclude in section 5.6 with some speculative thoughts on how an “economic singularity” might emerge.

## 5.2 How Artificial Intelligence Is Impacting the Production of Knowledge: Some Motivating Examples

Breakthroughs in AI are already impacting the productivity of scientific research and technology development. It is useful to distinguish between such meta technologies that aid in the process of search (knowledge access) and discovery (combining existing knowledge to produce new knowledge). For search, we are interested in AIs that solve problems that meet two conditions: (a) potential knowledge relevant to the process of discovery is subject to an explosion of data that an individual researcher or team of researchers finds increasingly difficult to stay abreast of (the “burden of knowledge”); and (b) the AI predicts which pieces of knowledge will be most relevant to the researcher, typically through the input of search terms. For discovery, we also identify two conditions: (a) potentially combinable knowledge for the production of new knowledge is subject to combinatorial explosion, and (b) the AI predicts which combinations of existing knowledge will yield valuable new knowledge across a large number of domains. We now consider some specific examples of how AI-based search and discovery technologies may change the innovation process.

### 5.2.1 Search

Meta<sup>a</sup> produces AI-based search technologies for identifying relevant scientific papers and tracking the evolution of scientific ideas. The company was acquired by the Chan-Zuckerberg Foundation, which intends to make it available free of charge to researchers. This AI-based search technology meets our two conditions for a meta technology for knowledge access: (a) the stock of scientific papers is subject to exponential growth at an estimated 8–9 percent per year (Bornmann and Mutz 2015), and (b) the AI-based search technology helps scientists identify relevant papers, thereby reducing the “burden of knowledge” associated with the exponential growth of published output.

BenchSci is an AI-based search technology for the more specific task of identifying effective compounds used in drug discovery (notably antibodies that act as reagents in scientific experiments). It again meets our two conditions: (a) reports on compound efficacy are scattered through millions of scientific papers with little standardization in how these reports are provided, and (b) an AI extracts compound-efficacy information, allowing scientists to more effectively identify appropriate compounds to use in experiments.

### 5.2.2 Discovery

Atomwise is a deep learning-based AI for the discovery of drug molecules (compounds) that have the potential to yield safe and effective new drugs. This AI meets our two conditions for a meta technology for discovery: (a) the number of potential compounds is subject to combinatorial explosion, and (b) the AI predicts how basic chemical features combine into more intricate features to identify potential compounds for more detailed investigation.

Deep Genomics is a deep learning-based AI that predicts what happens in a cell when DNA is altered by natural or therapeutic genetic variation. It again meets our two conditions: (a) genotype-phenotype variations are subject to combinatorial explosion, and (b) the AI “bridges the genotype-phenotype divide” by predicting the results of complex biological processes that relate variations in the genotype to observable characteristics of an organism, thus helping to identify potentially valuable therapeutic interventions for further testing.

## 5.3 A Combinatorial-Based Knowledge Production Function

Figure 5.1 provides an overview of our modeling approach and how it relates to the classic Romer/Jones knowledge production function. The solid lines capture the essential character of the Romer/Jones function. Researchers use existing knowledge—the standing-on-shoulders effect—to produce

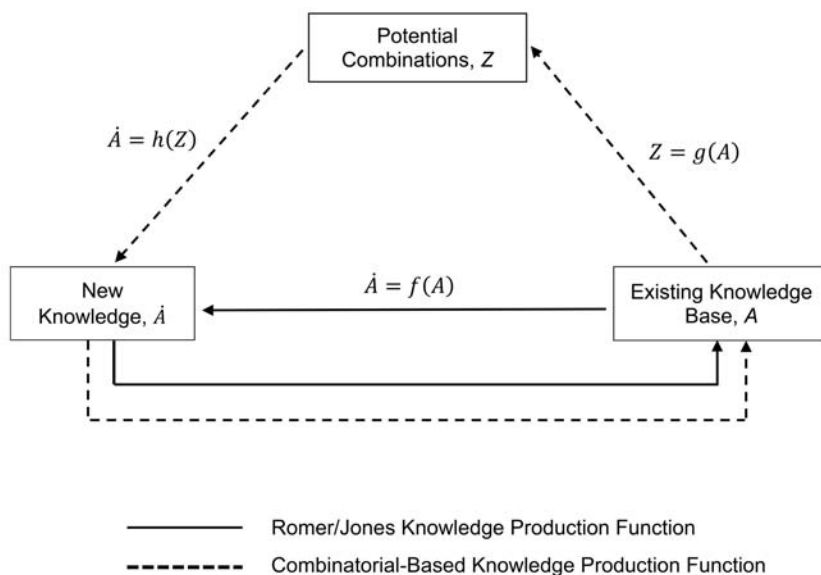


Fig. 5.1 Romer/Jones and combinatorial-based knowledge production functions

new knowledge. The new knowledge then becomes part of the knowledge base from which subsequent discoveries are made. The dashed lines capture our approach. The existing knowledge base determines the potential new combinations that are possible, the majority of which are likely to have no value. The discovery of valuable new knowledge is made by searching among the massive number of potential combinations. This discovery process is aided by meta technologies such as deep learning that allow researchers to identify valuable combinations in spaces where existing knowledge interacts in often highly complex ways. As with the Romer/Jones function, the new knowledge adds to the knowledge base—and thus the potential combinations of that knowledge base—which subsequent researchers have to work with. A feature of our new knowledge production function will be that the Romer/Jones function emerges as a limiting case both with and without team production of new knowledge. In this section, we first develop the new function without team production of new knowledge; in the next section, we extend the function to allow for team production.

The total stock of knowledge in the world is denoted as  $A$ , which we assume initially is measured discretely. An individual researcher has access to an amount of knowledge,  $A^\phi$  (also assumed to be an integer), so that the share of the stock of knowledge available to an individual researcher is  $A^{\phi-1}$ .<sup>2</sup> We assume that  $0 < \phi < 1$ . This implies that the share of total knowledge accessible to an individual researcher is falling with the total stock of knowledge. This is a manifestation in the model of the “burden of knowledge” effect identified by Jones (2009)—it becomes more difficult to access all the available knowledge as the total stock of knowledge grows. The knowledge access parameter,  $\phi$ , is assumed to capture not only what a researcher knows at a point in time, but also their ability to find existing knowledge should they require it. The value of the parameter will thus be affected by the extent to which knowledge is available in codified form and can be found as needed by researchers. The combination of digital repositories of knowledge and search technologies that can predict what knowledge will be most relevant to the researcher given the search terms they input—think of the ubiquitous Google as well as more specialized search technologies such as Meta<sup>α</sup> and BenchSci—should increase the value of  $\phi$ .

2. Paul Romer emphasized the importance of distinguishing between ideas (a nonrival good) and human capital (a rival good). “Ideas are . . . the critical input in the production of more valuable human and non-human capital. But human capital is also the most important input in the production of new ideas. . . . Because human capital and ideas are so closely related as inputs and outputs, it is tempting to aggregate them into a single type of good. . . . It is important, nevertheless, to distinguish ideas and human capital because they have different fundamental attributes as economic goods, with different implications for economic theory” (Romer 1993, 71). In our model,  $A^\phi$  is a measure of a researcher’s human capital. Clearly, human capital depends on the existing technological and other knowledge and the researcher’s access to that knowledge. In turn, the production of new knowledge depends on the researcher’s human capital.

Innovations occur as a result of combining existing knowledge to produce new knowledge. Knowledge can be combined  $a$  ideas at a time, where  $a = 0, 1 \dots A^\phi$ . For a given individual researcher, the total number of possible combinations of units of existing knowledge (including singletons and the null set)<sup>3</sup> given their knowledge access is

$$(1) \quad Z_i = \sum_{a=0}^{A^\phi} \binom{A^\phi}{a} = 2^{A^\phi}.$$

The total number of potential combinations,  $Z_i$ , grows exponentially with  $A^\phi$ . Clearly, if  $A$  is itself growing exponentially,  $Z_i$  will be growing at a double exponential rate. This is the source of combinatorial explosion in the model. Since it is more convenient to work with continuously measured variables in the growth model, from this point on we treat  $A$  and  $Z_i$  as continuously measured variables. However, the key assumption is that the number of potential combinations grows exponentially with knowledge access.

The next step is to specify how potential combinations map to discoveries. We assume that a large share of potential combinations do not produce useful new knowledge. Moreover, of those combinations that are useful, many will have already been discovered and thus are already part of  $A$ . This latter feature reflects the fishing-out phenomenon. The per-period translation of potential combinations into valuable new knowledge is given by the (asymptotically) constant elasticity discovery function

$$(2) \quad \dot{A}_i = \beta \left( \frac{Z_i^\theta - 1}{\theta} \right) = \beta \left( \frac{(2^{A^\phi})^\theta - 1}{\theta} \right) \quad \text{for } 0 < \theta \leq 1$$

$$= \beta \ln Z_i = \beta \ln(2^{A^\phi}) = \beta \ln(2) A^\phi \quad \text{for } \theta = 0,$$

where  $\beta$  is a positively valued knowledge discovery parameter and use is made of L'Hôpital's rule for the limiting case of  $\theta = 0$ .<sup>4</sup>

For  $\theta > 0$ , the elasticity of new discoveries with respect to the number of possible combinations,  $Z_i$ , is

$$(3) \quad \frac{\partial \dot{A}_i}{\partial Z_i} \frac{Z_i}{\dot{A}_i} = \frac{\beta Z_i^{\theta-1}}{\beta [(Z_i^\theta - 1) / \theta]} = \left( \frac{Z_i^\theta}{Z_i^\theta - 1} \right) \theta,$$

3. Excluding the singletons and the null set, total number of potential combinations would be  $2^{A^\phi} - A^\phi - 1$ . As singletons and the null set are not true "combinations," we take equation (1) to be an approximation of the true number of potential combinations. The relative significance of this approximation will decline as the knowledge base grows, and we ignore it in what follows.

4. L'Hôpital's rule is often useful where a limit of a quotient is indeterminate. The limit of the term in brackets on the right-hand side of equation (2) as  $\theta$  goes to zero is 0 divided by 0 and is thus indeterminate. However, by L'Hôpital's rule, the limit of this quotient is equal to the limit of the quotient produced by dividing the limit of the derivative of the numerator with respect to  $\theta$  by the limit of the derivative of the denominator with respect to  $\theta$ . This limit is equal to  $\ln(2)A^\phi$ .

which converges to  $\theta$  as the number of potential combinations goes to infinity. For  $\theta = 0$ , the elasticity of new discoveries is

$$(4) \quad \frac{\partial \dot{A}}{\partial Z_i} \frac{Z_i}{\dot{A}} = \frac{\beta}{Z_i} \frac{Z_i}{\beta \ln Z_i} = \frac{1}{\ln Z_i},$$

which converges to zero as the number of potential combinations goes to infinity.

A number of factors seem likely to affect the value of the fishing-out/complexity parameter,  $\theta$ . First are basic constraints relating to natural phenomena that limit what is physically possible in terms of combining existing knowledge to produce scientifically or technologically useful new knowledge. Pessimistic views on the possibilities for future growth tend to emphasize such constraints. Second is the ease of discovering new useful combinations that are physically possible. The potentially massive size and complexity of the space of potential combinations means that finding useful combinations can be a needle-in-the-haystack problem. Optimistic views of the possibilities for future growth tend to emphasize how the combination of AI (embedded in algorithms such as those developed by Atomwise and DeepGenomics) and increases in computing power can aid prediction in the discovery process, especially where it is difficult to identify patterns of cause and effect in high-dimensional data. Third, recognizing that future opportunities for discoveries are path dependent (see, e.g., Weitzman 1998), the value of  $\theta$  will depend on the actual path that is followed. To the extent that AI can help identify productive paths, it will limit the chances of economies going down technological dead ends.

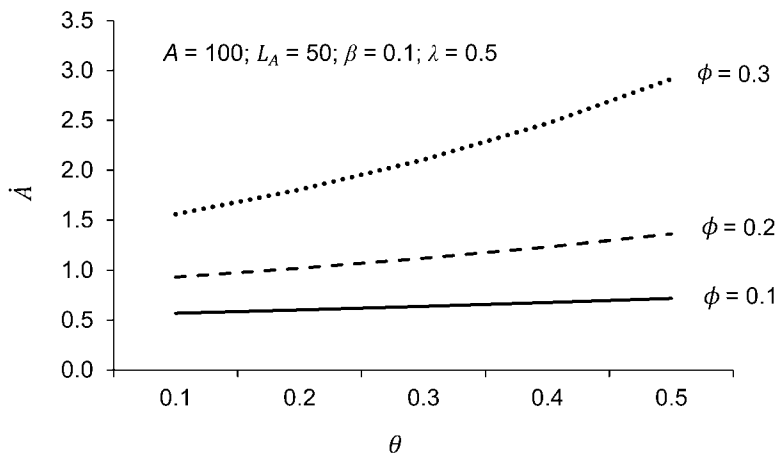
There are  $L_A$  researchers in the economy each working independently, where  $L_A$  is assumed to be measured continuously. (In section 5.4, we consider the case of team production in an extension of the model.) We assume that some researchers will duplicate each other's discoveries—the standing-on-toes effect. To capture this effect, new discoveries are assumed to take place “as if” the actual number of researchers is equal to  $L_A^\lambda$ , where  $0 \leq \lambda \leq 1$ . Thus the aggregate knowledge production function for  $\theta > 0$  is given:

$$(5) \quad \dot{A} = \beta L_A^\lambda \left( \frac{(2^{A^\theta})^\theta - 1}{\theta} \right).$$

At a point in time (with given values of  $A$  and  $L_A$ ), how does an increase in  $\theta$  affect the rate of discovery of new knowledge,  $\dot{A}$ ? The partial derivative of  $\dot{A}$  with respect to  $\theta$  is

$$(6) \quad \frac{\partial \dot{A}}{\partial \theta} = \frac{\beta L_A^\lambda (\theta \ln(2) A^\theta - 1) 2^{A^\theta}}{\theta^2} + \frac{\beta L_A^\lambda}{\theta^2}.$$

A sufficient condition for this partial derivative to be positive is that that term in square brackets is greater than zero, which requires



**Fig. 5.2** Relationships between new knowledge production,  $\theta$ , and  $\phi$

$$(7) \quad A > \left( \frac{1}{\theta \ln(2)} \right)^{1/\phi}.$$

We assume this condition holds. Figure 5.2 shows an example of how  $\dot{A}$  (and also the percentage growth of  $A$  given that  $A$  is assumed to be equal to 100) varies with  $\theta$  for different assumed values of  $\phi$ . Higher values of  $\theta$  are associated with a faster growth rate. The figure also shows how  $\theta$  and  $\phi$  interact positively: greater knowledge access (as reflected in a higher value of  $\phi$ ) increases the gain associated with a given increase in the value of  $\theta$ .

We assume, however, that  $\theta$  itself evolves with  $A$ . A larger  $A$  means a bigger and more complex discovery search space. We further assume that this complexity will eventually overwhelm any discovery technology given the power of the combinatorial explosion as  $A$  grows. This is captured by assuming that  $\theta$  is a declining function of  $A$ ; that is,  $\theta = \theta(A)$ , where  $\theta'(A) < 0$ . In the limit as  $A$  goes to infinity, we assume that  $\theta(A)$  goes to zero, or

$$(8) \quad \lim_{A \rightarrow \infty} \theta(A) = 0.$$

This means that the discovery function converges asymptotically (given sustained growth in  $A$ ) to

$$(9) \quad \dot{A} = \beta \ln(2) L_A^\lambda A^\phi.$$

This mirrors the functional form of the Romer/Jones function and allows for decreasing returns to scale in the number of researchers, depending on the size of  $\lambda$ . While the form of the function is familiar by design, its combinatorial-based foundations have the advantage of providing richer motivations for the key parameters in the knowledge discovery function.

We use the fact that the functional form of equation (9) is the same as that used in Jones (1995) to solve for the steady state of the model. More precisely, given that the limiting behaviour of our knowledge production function mirrors the function used by Jones and all other aspects of the economy are assumed to be identical, the steady state along a balanced growth path with constant exponential growth will be the same as in that model.

As we have nothing to add to the other elements of the model, we here simply sketch the growth model developed by Jones (1995), referring the reader to the original for details. The economy is composed of a final goods sector and a research sector. The final goods sector uses labor,  $L_Y$ , and intermediate inputs to produce its output. Each new idea (or “blueprint”) supports the design of an intermediate input, with each input being supplied by a profit-maximizing monopolist. Given the blueprint, capital,  $K$ , is transformed unit for unit in producing the input. The total labor force,  $L$ , is fully allocated between the final goods and research sectors, so that  $L_Y + L_A = L$ . We assume the labor force to be equal to the population and growing at rate  $n(>0)$ .

Building on Romer (1990), Jones (1995) shows that the production function for final goods can be written as

$$(10) \quad Y = (AL_Y)^\alpha K^{1-\alpha},$$

where  $Y$  is final goods output. The intertemporal utility function of a representative consumer in the economy is given by

$$(11) \quad U = \int_0^\infty u(c)e^{-\rho t} dt,$$

where  $c$  is per capita consumption and  $\rho$  is the consumer’s discount rate. The instantaneous utility function is assumed to exhibit constant relative risk aversion, with a coefficient of risk aversion equal to  $\sigma$  and a (constant) intertemporal elasticity of substitution equal to  $1/\sigma$ .

Jones (1995) shows that the steady-state growth rate of this economy along a balanced growth path with constant exponential growth is given by

$$(12) \quad g_A = g_y = g_c = g_k = \frac{\lambda n}{1 - \phi},$$

where  $g_A = \dot{A}/A$  is the growth rate of the knowledge stock,  $g_y$  is the growth rate of per capita output  $y$ , (where  $y = Y/L$ ),  $g_c$  is the growth rate of per capita output  $c$  (where  $c = C/L$ ), and  $g_k$  is the growth rate of the capital labor ratio (where  $k = K/L$ ).

Finally, the steady-state share of labor allocated to the research sector is given by

$$(13) \quad s = \frac{1}{1 + \left\{ 1 / \left[ \lambda(\rho(1 - \phi) / \lambda n) + (1 / \sigma) - \phi \right] \right\}}.$$



We can now consider how changes in the parameters of knowledge production given by equation (5) will affect the dynamics of growth in the economy. We start with improvement in the availability of AI-based search technologies that improve a researcher's access to knowledge. In the context of the model, the availability of AI-based search technologies—for example, Google, Meta<sup>a</sup>, BenchSci, and so forth—should increase the value of  $\phi$  and reduce the “burden of knowledge” effect. From equation (12), an increase in this parameter will increase the steady-state growth rate and also the growth rate and the level of per capital output along the transition path to the steady state.

We next consider AI-based technologies that increase the value of the discovery parameter,  $\beta$ . As  $\beta$  does not appear in the steady state in equation (12), the steady-state growth rate is unaffected. However, such an increase will raise the growth rate (and level) along the path to that steady state.

The most interesting potential changes to the possibilities for growth come about if we allow a change to the fishing-out/complexity parameter,  $\theta$ . We assume that the economy is initially in a steady state and then experiences an increase in  $\theta$  as the result of the discovery of a new AI technology. Recall that we assume that  $\theta$  will eventually converge back to zero as the complexity that comes with combinatorial explosion eventually overwhelms the new AI. Thus, the steady state of the economy is unaffected. However, the transition dynamics are again quite different, with larger increases in knowledge for an given starting of the knowledge stock along the path back to the steady state.

Using Jones (1995) as the limiting case of the model is appealing because we avoid unbounded increases in the growth rate, which would lead to the breakdown of any reasonable growth model and indeed a breakdown in the normal operations of any actual economy. It is interesting to note, however, what happens to growth in the economy if instead of assuming that  $\theta$  converges asymptotically to zero, it stays at some positive value (even if very small). Dividing both sides of equation (5) by  $A$  gives an expression for the growth rate of the stock of knowledge

$$(14) \quad \frac{\dot{A}}{A} = \frac{\beta \ln(2) L_A^\lambda}{A} \left( \frac{(2^{A^\phi})^\theta - 1}{\theta} \right).$$

The partial derivative of this growth rate with respect to  $A$  is

$$(15) \quad \frac{\partial(\dot{A}/A)}{\partial A} = \frac{L_A^\lambda \beta}{\theta A^2} \left[ 1 + (2^{A^\phi})^\theta (\phi \theta \ln(2) A^\phi - 1) \right].$$

The key to the sign of this derivative is the sign of the term inside the last round brackets. This term will be positive for a large enough  $A$ . As  $A$  is growing over time (for any positive number of researchers and existing knowledge stock), the growth rate must eventually begin to rise once  $A$  exceeds some threshold value. Thus, with a fixed positive value of  $\theta$  (or with  $\theta$  converging

asymptotically to a positive value), the growth rate will eventually begin to grow without bound.

A possible deeper foundation for our combinatorial-based knowledge production function is provided by the work on “rugged landscapes” (Kauffman 1993). Kauffman’s NK model has been fruitfully applied to questions of organizational design (Levinthal 1997), strategy (Rivkin 2000) and science-driven technological search (Fleming and Sorenson 2004). In our setting, each potential combination of existing ideas accessible to a researcher is a point in the landscape represented by a binary string indicating whether each idea in the set of accessible knowledge is in the combination (a 1 in the string) or not (a 0 in the string). The complexity—or “ruggedness”—of the landscape depends on the total number of ideas that can be combined and also on the way that the elements of the binary string interact. For any given element, its impact on the value of the combination will depend on the value of  $X$  other elements.<sup>5</sup> The larger the value of  $X$  the more interrelated are the various elements of the string, creating a more rugged knowledge landscape and thus a harder the search problem for the innovator.

We can think of would-be innovators as starting from some already known valuable combination and searching for other valuable combinations in the vicinity of that combination (see, e.g., Nelson and Winter 1982). Purely local search can be thought of as varying one component of the binary string at a time for some given fraction of the total elements of the string. This implies that the total number of combinations that can be searched is a linear function of the innovator’s knowledge. This is consistent with the Romer/Jones knowledge production function where the discovery of new knowledge is a linear function of knowledge access,  $A^f$ . Positive values of  $\theta$  are then associated with the capacity to search a larger fraction of the space of possible combinations, which in turn increases the probability of discovering a valuable combination. Meta technologies such as deep learning can be thought of as expanding the capacity to search a given space of potential combinations—that is, as increasing the value of  $\theta$ —thereby increasing the chance of new discoveries. Given its ability to deal with complex nonlinear spaces, deep learning may be especially valuable for search over highly rugged landscapes.

#### 5.4 A Combinatorial-Based Knowledge Production Function with Team Production: An Extended Model

Our basic model assumes that researchers working alone combine the knowledge to which they have access,  $A^b$ , to discover new knowledge. In reality, new discoveries are increasingly being made by research teams (Jones 2009; Nielsen 2012; Agrawal, Goldfarb, and Teodoridis 2016). Assuming

5.  $K$  elements in Kauffman’s original notation.

initially no redundancy in the knowledge that individual members bring to the team—that is, collective team knowledge is the sum of the knowledge of the individual team members—combining individual researchers into teams can greatly expand the knowledge base from which new combinations of existing knowledge can be made. This also opens up the possibility of a positive interaction between factors that facilitate the operation of larger teams and factors that raise the size of the fishing-out/complexity parameter,  $\theta$ . New meta technologies such as deep learning can be more effective in a world where they are operating on a larger knowledge base due to the ability of researchers to more effectively pool their knowledge by forming larger teams.

We thus extend in this section the basic model to allow for new knowledge to be discovered by research teams. For a team with  $m$  members and no overlap in the knowledge of its members, the total knowledge access for the team is simply  $mA^\phi$ . (We later relax the assumption of no knowledge overlap within a team.) Innovations occur as a result of the team combining existing knowledge to produce new knowledge. Knowledge can be combined by the team  $a$  ideas at a time, where  $a = 0, 1 \dots mA^\phi$ . For a given team  $j$  with  $m$  members, the total number of possible combinations of units of existing knowledge (including singletons and the null set) given their combined knowledge access is

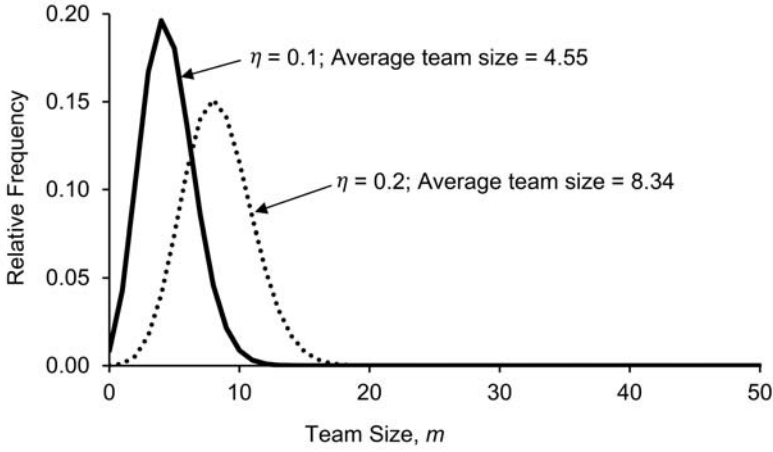
$$(16) \quad Z_j = \sum_{a=0}^{mA^\phi} \binom{mA^\phi}{a} = 2^{mA^\phi}.$$

Assuming again for convenience that  $A^\phi$  and  $Z$  can be treated as continuous, the per-period translation of potential combinations into valuable new knowledge by a team is again given by the (asymptotic) constant elasticity discovery function

$$(17) \quad \begin{aligned} \dot{A}_j &= \beta \left( \frac{Z_j^\theta - 1}{\theta} \right) = \beta \left( \frac{(2^{mA^\phi})^\theta - 1}{\theta} \right) \text{ for } 0 < \theta \leq 1 \\ &= \beta \ln Z_j = \beta \ln(2^{mA^\phi}) = \beta \ln(2)mA^\phi \text{ for } \theta = 0, \end{aligned}$$

where use is again made of L'Hôpital's rule for the limiting case of  $\theta = 0$ .

The number of researchers in the economy at a point in time is again  $L_A$  (which we now assume is measured discretely). Research teams can potentially be formed from any possible combination of the  $L_A$  researchers. For each of these potential teams, a entrepreneur can coordinate the team. However, for a potential team with  $m$  members to form, the entrepreneur must have relationships with all  $m$  members. The need for a relationship thus places a constraint on feasible teams. The probability of a relationship existing between the entrepreneur and any given researcher is  $\eta$ , and thus the probability of relationships existing between all members of a team of size  $m$  is  $\eta^m$ . Using the formula for a binomial expansion, the expected total number of feasible teams is



**Fig. 5.3** Example of how the distribution of team size varies with  $\eta$

$$(18) \quad S = \sum_{m=0}^{L_A} \binom{L_A}{m} \eta^m = (1 + \eta)^{L_A}.$$

The average feasible team size is then given by

$$(19) \quad \bar{m} = \frac{\sum_{m=0}^{L_A} \binom{L_A}{m} \eta^m m}{\sum_{m=0}^{L_A} \binom{L_A}{m} \eta^m}.$$

Factorizing the numerator and substituting in the denominator using equation (18), we obtain a simple expression for the average feasible team size:

$$(20) \quad \bar{m} = \frac{\sum_{m=0}^{L_A} \binom{L_A}{m} \eta^m m}{\sum_{m=0}^{L_A} \binom{L_A}{m} \eta^m} = \frac{(1 + \eta)^{L_A-1} \eta L_A}{(1 + \eta)^{L_A}} = \left( \frac{\eta}{1 + \eta} \right) L_A.$$

Figure 5.3 shows an example of the full distribution of teams sizes (with  $L_A = 50$ ) for two different values of  $\eta$ . An increase in  $\eta$  (i.e., an improvement in the capability to form teams) will push the distribution to the right and increase the average team size.

We can now write down the form that the knowledge production function would take if all possible research teams could form (ignoring for the moment any stepping-on-toes effects):

$$(21) \quad \dot{A} = \left( \sum_{m=0}^{L_A} \binom{L_A}{m} \eta^m \beta \frac{(2^{m_A^\theta})^\theta - 1}{\theta} \right) \text{ for } 0 < \theta \leq 1.$$

We next allow for the fact that only a fraction of the feasible teams will actually form. Recognising obvious time constraints on the ability of a given researcher to be part of multiple research teams, we impose the constraint that each researcher can only be part of one team. However, we assume the size of any team that successfully forms is drawn from the same distribution over sizes as the potential teams. Therefore, the expected average team size is also given by equation (18). With this restriction, we can solve for the total number of teams,  $N$ , from the equation  $L_A = N[\eta/(1 + \eta)]L_A$ , which implies  $N = (1 + \eta)/\eta$ .

Given the assumption that the distribution of actual team sizes is drawn from the same distribution as the feasible team sizes, the aggregate knowledge production function (assuming  $\theta > 0$ ) is then given by

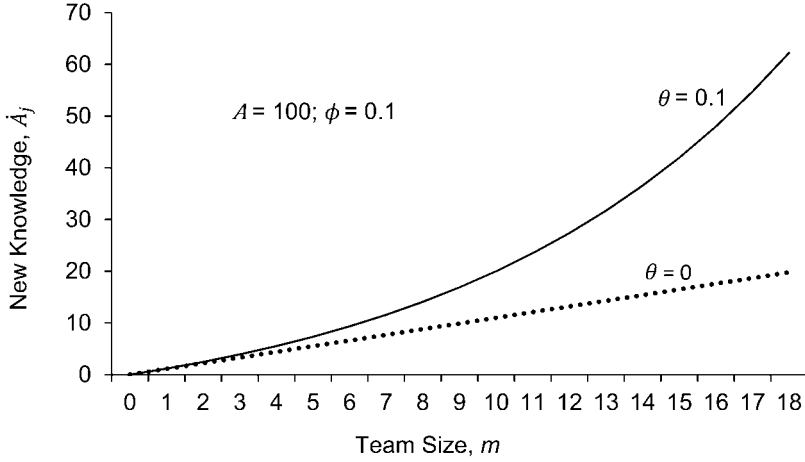
$$(22) \quad \begin{aligned} \dot{A} &= \frac{(1 + \eta) / \eta}{(1 + \eta)^{L_A}} \left( \sum_{m=0}^{L_A} \binom{L_A}{m} \eta^m \beta \frac{(2^{mA^\phi})^\theta - 1}{\theta} \right) \\ &= \frac{1}{(1 + \eta)^{L_A-1} \eta} \left( \sum_{m=0}^{L_A} \binom{L_A}{m} \eta^m \beta \frac{(2^{mA^\phi})^\theta - 1}{\theta} \right), \end{aligned}$$

where the first term is the actual number of teams as a fraction of the potentially feasible number of teams. For  $\theta = 0$  the aggregate knowledge production function takes the form

$$(23) \quad \begin{aligned} \dot{A} &= \frac{1}{(1 + \eta)^{L_A-1} \eta} \left( \sum_{m=0}^{L_A} \binom{L_A}{m} \eta^m m \beta \ln(2) A^\phi \right) \\ &= \frac{1}{(1 + \eta)^{L_A-1} \eta} \left( (1 + \eta)^{L_A-1} \eta L_A \beta \ln(2) A^\phi \right) \\ &= \beta L_A \ln(2) A^\phi. \end{aligned}$$

To see intuitively how an increase in  $\eta$  could affect aggregate knowledge discovery when  $\theta > 0$ , note that from equation (20) an increase in  $\eta$  will increase the average team size of the teams that form. From equation (16), we see that for a given knowledge access by an individual researcher, the number of potential combinations increases exponentially with the size of the team,  $m$  (see figure 5.4). This implies that combining two teams of size  $m'$  to create a team of size  $2m'$  will more than double the new knowledge output of the team. Hence, there is a positive interaction between  $\theta$  and  $\eta$ . On the other hand, when  $\theta = 0$ , combining the two teams will exactly double the new knowledge output given the linearity of the relationship between team size and knowledge output. In this case, the aggregate knowledge is invariant to the distribution of team sizes.

To see this formally, note that from equation (23) we know that when  $\theta = 0$ , the partial derivative of  $\dot{A}$  with respect to  $\eta$  must be zero since  $\eta$  does not appear in the final form of the knowledge production function. This results



**Fig. 5.4** Team knowledge production and team size

from the balancing of two effects as  $\eta$  increases. The first (negative) effect is that the number of teams as a share of the potentially possible teams falls. The second (positive) effect is that the amount of new knowledge production if all possible teams do form rises. We can now ask what happens if we raise  $\theta$  to a strictly positive value. The first of these effects is unchanged. But that second effect will be stronger provided that the knowledge production of a team for any given team size rises with  $\theta$ . A sufficient condition for this to be true is that

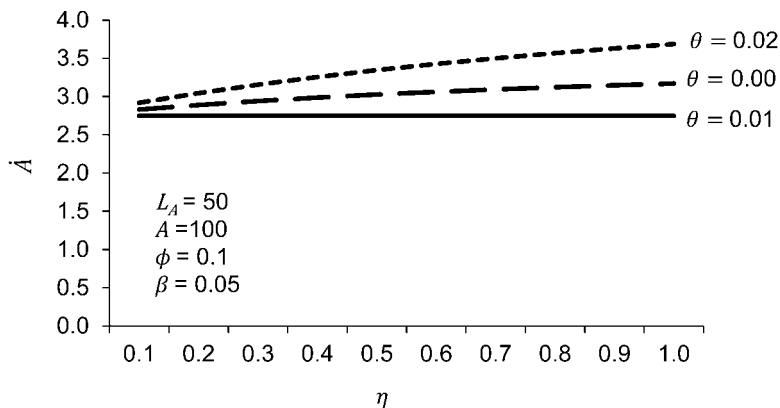
$$(24) \quad A > \left( \frac{1}{\theta \ln(2)m} \right)^{1/\phi} \text{ for all } m > 0.$$

We assume that the starting size of the knowledge stock is large enough so that this condition holds. Moreover, the partial derivative of  $\dot{A}$  with respect to  $\eta$  will be larger the larger is the value of  $\theta$ . We show these effects for a particular example in figure 5.5.

The possibilities of knowledge overlap at the level of the team and duplication of knowledge outputs between teams creates additional complications. To allow for stepping-on-toes effects, it is useful to first rewrite equation (20) as

$$(25) \quad \dot{A} = \left( \frac{1+\eta}{\eta} \right) \left( \frac{\eta}{1+\eta} \right)^{L_A} \frac{1}{(1+\eta)^{L_A-1} \eta^{L_A}} \left( \sum_{m=0}^{L_A} \binom{L_A}{m} \eta^m \beta \frac{(2^{mA^\theta})^\theta - 1}{\theta} \right).$$

We introduce two stepping-on-toes effects. First, we allow for knowledge overlap within teams to introduce the potential for redundancy of knowledge. A convenient way to introduce this effect is to assume that the overlap



**Fig. 5.5** Relationships between new knowledge production,  $\eta$ , and  $\theta$

reduces the *effective* average team size in the economy from the viewpoint of generating new knowledge. More specifically, we assume the effective team size is given by

$$(26) \quad \bar{m}^e = \bar{m}^\gamma = \left( \left( \frac{\eta}{1+\eta} \right) L_A \right)^\gamma,$$

where  $0 \leq \gamma \leq 1$ . The extreme case of  $\gamma = 0$  (full overlap) has each team acting as if it had effectively a single member; the opposite extreme of  $\gamma = 1$  (no overlap) has no knowledge redundancy at the level of the team. Second, we allow for the possibility that new ideas are duplicated across teams. The effective number of non-idea-duplicating teams is given by

$$(27) \quad N^e = N^{1-\psi} = \left( \frac{1+\eta}{\eta} \right)^{1-\psi},$$

where  $0 \leq \psi \leq 1$ . The extreme case of  $\psi = 0$  (no duplication) implies that the effective number of teams is equal to the actual number of teams; the extreme case of  $\psi = 1$  (full duplication) implies that a single team produces the same number of new ideas as the full set of teams.

We can now add the stepping-on-toes effects—knowledge redundancy within teams and discovery duplication between teams—to yield the general form of the knowledge production function for  $\theta > 0$ :

$$(28) \quad \dot{A} = \left( \frac{1+\eta}{\eta} \right)^{1-\psi} \left( \left( \frac{\eta}{1+\eta} \right) L_A \right)^\gamma \frac{1}{(1+\eta)^{L_A-1} \eta L_A} \left( \sum_{m=0}^{L_A} \binom{L_A}{m} \eta^m \beta \frac{(2^{mA^\phi})^\theta - 1}{\theta} \right).$$

If we take the limit of equation (24) as  $\theta$  goes to zero, we reproduce the limiting case of the knowledge production function. Ignoring integer constraints on  $L_A$ , this knowledge production function again has the form of the Romer/Jones function:

$$\begin{aligned}
(29) \quad \dot{A} &= \left( \frac{1+\eta}{\eta} \right)^{1-\psi} \left( \left( \frac{\eta}{1+\eta} \right) L_A \right)^\gamma \frac{1}{(1+\eta)^{L_A-1} \eta L_A} \left( \sum_{m=0}^{L_A} \binom{L_A}{m} \eta^m \beta \ln(2) m A^\phi \right) \\
&= \left( \frac{1+\eta}{\eta} \right)^{1-\psi} \left( \left( \frac{\eta}{1+\eta} \right) L_A \right)^\gamma \frac{(1+\eta)^{L_A-1} \eta L_A}{(1+\eta)^{L_A-1} \eta L_A} \beta \ln(2) A^\phi \\
&= \left( \frac{1+\eta}{\eta} \right)^{1-\psi} \left( \left( \frac{\eta}{1+\eta} \right) \right)^\gamma \beta \ln(2) L_A^\gamma A^\phi.
\end{aligned}$$

We note finally the presence of the relationship parameter  $\eta$  in the knowledge production equation. This can be taken to reflect in part the importance of (social) relationships in the forming of research teams. Advances in computer-based technologies such as email and file sharing (as well as policies and institutions) could also affect this parameter (see, e.g., Agrawal and Goldfarb [2008] on the effects of the introduction of precursors to today's internet on collaboration between researchers). Although not the main focus of this chapter, being able to incorporate the effects of changes in collaboration technologies increases the richness of the framework for considering the determinants of the efficiency of knowledge production.

## 5.5 Discussion

### 5.5.1 Something New under the Sun? Deep Learning as a New Tool for Discovery

Two key observations motivate the model developed above. First, using the analogy of finding a needle in a haystack, significant obstacles to discovery in numerous domains of science and technology result from highly nonlinear relationships of causes and effect in high-dimensional data. Second, advances in algorithms such as deep learning (combined with increased availability of data and computing power) offer the potential to find relevant knowledge and predict combinations that will yield valuable new discoveries.

Even a cursory review of the scientific and engineering literatures indicates that needle-in-the-haystack problems are pervasive in many frontier fields of innovation, especially in areas where matter is manipulated at the molecular or submolecular level. In the field of genomics, for example, complex genotype-phenotype interactions make it difficult to identify therapies that yield valuable improvements in human health or agricultural productivity. In the field of drug discovery, complex interactions between drug compounds and biological systems present an obstacle to identifying promising new drug therapies. And in the field of material sciences, including nanotechnology, complex interactions between the underlying physical and chemical mechanisms increases the challenge of predicting the performance of potential new materials with potential applications ranging from new



materials to prevent traumatic brain injury to lightweight materials for use in transportation to reduce dependence on carbon-based fuels (National Science and Technology Council 2011).

The apparent speed with which deep learning is being applied in these and other fields suggests it represents a breakthrough general purpose meta technology for predicting valuable new combinations in highly complex spaces. Although an in-depth discussion of the technical advances underlying deep learning is beyond the scope of this chapter, two aspects are worth highlighting. First, previous generations of machine learning were constrained by the need to extract features (or explanatory variables) by hand before statistical analysis. A major advance in machine learning involves the use of “representation learning” to automatically extract the relevant features.<sup>6</sup> Second, the development and optimization of multilayer neural networks allows for substantial improvement in the ability to predict outcomes in high-dimensional spaces with complex nonlinear interactions (LeCun, Bengio, and Hinton 2015). A recent review of the use of deep learning in computational biology, for instance, notes that the “rapid increase in biological data dimensions and acquisition rates is challenging conventional analysis strategies,” and that “[m]odern machine learning methods, such as deep learning, promise to leverage very large data sets for finding hidden structure within them, and for making accurate predictions” (Angermueller et al. 2016, 1). Another review of the use of deep learning in computational chemistry highlights how deep learning has a “ubiquity and broad applicability to a wide range of challenges in the field, including quantitative activity relationship, virtual screening, protein structure prediction, quantum chemistry, materials design and property prediction” (Goh, Hodas, and Vishu 2017).

Although the most publicized successes of deep learning have been in areas such as image recognition, voice recognition, and natural language processing, parallels to the way in which the new methods work on unstructured data are increasingly being identified in many fields with similar data challenges to produce research breakthroughs.<sup>7</sup> While these new general purpose research tools will not displace traditional mathematical models of

6. As described by LeCun, Bengio, and Hinton (2015, 436), “[c]onventional machine-learning techniques were limited in their ability to process natural data in their raw form. For decades, constructing a pattern-recognition or machine-learning system required careful engineering and considerable domain expertise to design a feature extractor that transformed the raw data (such as the pixel values of an image) into a suitable internal representation or feature vector from which the learning subsystem, often a classifier, could detect or classify patterns in the input. . . . Representation learning is a set of methods that allows a machine to be fed with raw data and to automatically discover the representations needed for detection or classification.”

7. A recent review of deep-learning applications in biomedicine usefully draws out these parallels: “With some imagination, parallels can be drawn between biological data and the types of data deep learning has shown the most success with—namely image and voice data. A gene expression profile, for instance, is essentially a ‘snapshot,’ or image, of what is going on in a given cell or tissue in the same way that patterns of pixilation are representative of the objects in a picture” (Mamoshina et al. 2016, 1445).

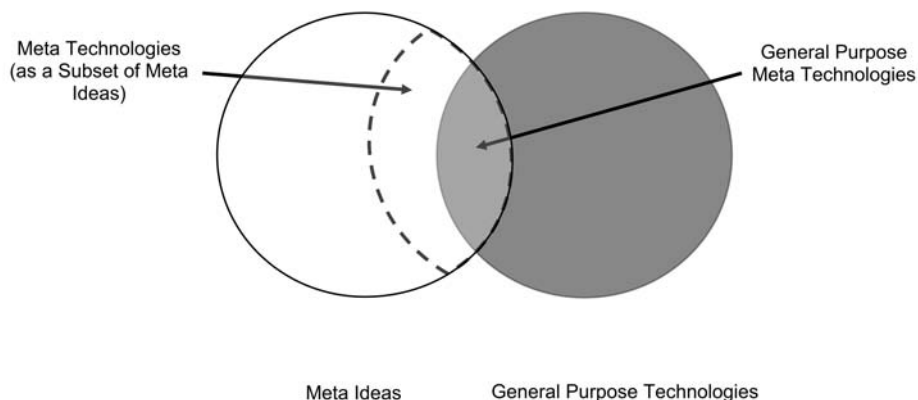
cause and effect and careful experimental design, machine-learning methods such as deep learning offer a promising new tool for discovery—including hypothesis generation—where the complexity of the underlying phenomena present obstacles to more traditional methods.<sup>8</sup>

### 5.5.2 Meta Ideas, Meta Technologies, and General Purpose Technologies

We conceptualize AIs as general purpose meta technologies—that is, general purpose technologies (GPTs) for the discovery of new knowledge. Figure 5.6 summarises the relationship between Paul Romer’s broader idea of meta ideas, meta technologies, and GPTs. Romer defines a meta idea as an idea that supports the production and transmission of other ideas (see, e.g., Romer 2008). He points to such ideas as the patent, the agricultural extension station, and the peer-review system for research grants as examples of meta ideas. We think of meta technologies as a subset of Romer’s meta ideas (the area enclosed by the dashed lines in figure 5.6), where the idea for how to discover new ideas is embedded in a technological form such as an algorithm or measurement instrument.

Elhanan Helpman (1998, 3) argues that a “drastic innovation qualifies as a GPT if it has the potential for pervasive use in a wide range of sectors in ways that drastically change their mode of operation.” He further notes two important features necessary to qualify as a GPT: “generality of purpose and innovational complementarities” (see also Bresnahan and Trajtenberg 1995). Not all meta technologies are general purpose in this sense. The set of general purpose meta technologies is given by the intersection of the two circles in figure 5.6. Cockburn, Henderson, and Stern (chapter 4, this volume) give the example of functional MRI as an example of a discovery tool that lacks the generality of purpose required for a GPT. In contrast, the range of application of deep learning as a discovery tool would appear to qualify it as a GPT. It is worth noting that some authors discuss GPTs as technologies that more closely align with our idea of a meta technology. Rosenberg (1998), for example, provides a fascinating examination of chemical engineering as an example of GPT. Writing of this branch of engineering, he argues that a “discipline that provides the concepts and methodologies to generate new or improved technologies over a wide range of downstream economic activity may be thought of as an even purer, or higher order, GPT” (Rosenberg 1998, 170).

8. A recent survey of the emerging use of machine learning in economics (including policy design) provides a pithy characterization of the power of the new methods: “The appeal of machine learning is that it manages to uncover generalizable patterns. In fact, the success of machine learning at intelligence tasks is largely due to its ability to discover complex structure that was not specified in advance. It manages to fit complex and very flexible functional forms to the data without simply overfitting; it finds functions that work well out of sample” (Mullainathan and Spiess 2017, 88).



**Fig. 5.6 Relationships between meta ideas, meta technologies, and general purpose technologies**

Our concentration on general purpose meta technologies (GPMTs) parallels Cockburn, Henderson, and Stern’s (chapter 4, this volume) idea of a general purpose invention of a method of invention. This idea combines the idea of a GPT with Zvi Griliches’ (1957) idea of the “invention of a method of invention,” or IMI. Such an invention has the “potential for a more influential impact than a single invention, but is also likely to be associated with a wide variation in the ability to adapt the new tool to particular settings, resulting in a more heterogeneous pattern of diffusion over time” (Cockburn, Henderson, and Stern, chapter 4, this volume). They see some emerging AIs such as deep learning as candidates for such general purpose IMIs and contrast these with AIs underpinning robotics that, while being GPTs, do not have the characteristic features of an IMI.

### 5.5.3 Beyond AI: Potential Uses of the New Knowledge Production Function

Although the primary motivation for this chapter is to explore how breakthroughs in AI could affect the path of economic growth, the knowledge production function we develop is potentially of broader applicability. By deriving the Romer/Jones knowledge production function as the limiting case of a more general function, our analysis may also contribute to providing candidate microfoundations for that function.<sup>9</sup> The key conceptual

9. In developing and applying the Romer/Jones knowledge production function, growth theorists have understood its potential combinatorial underpinnings and the limits of the Cobb-Douglas form. Charles Jones (2005) observes in his review chapter on “Growth and Ideas” for the *Handbook of Economic Growth*: “While we have made much progress in understanding economic growth in a world where ideas are important, there remain many open, interesting research questions. The first is ‘What is the shape of the idea production function?’ How do

change is to model discovery as operating on the space of potential combinations (rather than directly on the knowledge base itself). As in Weitzman (1998), our production function focuses attention explicitly on how new knowledge is discovered by combining existing knowledge, which is left implicit in the Romer/Jones formulation. While this shift in emphasis is motivated by the particular way in which deep learning can aid discovery—allowing researchers to uncover otherwise hard-to-find valuable combinations in highly complex spaces—the view of discovery as the innovative combination of what is already known has broader applicability. The more general function also has the advantage of providing a richer parameter space for mapping how meta technologies or policies could affect knowledge discovery. The  $\phi$  parameter captures how access to knowledge at the individual researcher level determines the potential for new combinations to be made given the inherited knowledge base. The  $\theta$  parameter captures how the available potential combinations (given the access to knowledge) map to new discoveries. Finally, the  $\eta$  parameter captures the ease of forming research teams and ultimately the average team size. To the extent that the capacity to bring the knowledge of individual researchers together through research teams directly affects the possible combinations, the ease of team formation can have an important effect on how the existing knowledge base is utilized for new knowledge discovery.

We hope this more general function will be of use in other contexts. In a recent commentary celebrating the twenty-fifth anniversary of the publication of Romer (1990), Joshua Gans (2015) observes that the Romer growth model has not been as influential on the design of growth policy as might have been expected despite its enormous influence on the subsequent growth theory literature. The reason he identifies is that it abstracts away “some of the richness of the microeconomy that give rise to new ideas and also their dissemination” (Gans 2015). By expanding the parameter space, our function allows for the inclusion of more of this richness, including the role that meta technologies such as deep learning can play in knowledge access and knowledge discovery, but potentially other policy and institutional factors that affect knowledge access, discovery rates, and team formation as well.

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ideas get produced? The combinatorial calculations of Romer (1993) and Weitzman (1998) are fascinating and suggestive. The current research practice of modelling the idea production function as a stable Cobb-Douglas combination of research and the existing stock of ideas is elegant, but at this point we have little reason to believe it is correct. One insight that illustrates the incompleteness of our knowledge is that there is no reason why research productivity should be a smooth monotonic function of the stock of ideas. One can easily imagine that some ideas lead to domino-like unravelling of phenomena that were previously mysterious . . . Indeed, perhaps decoding of the human genome or the continued boom in information technology will lead to a large upward shift in the production function for ideas. On the other hand, one can equally imagine situations where research productivity unexpectedly stagnates, if not forever then at least for a long time” (Jones 2005, 1107).

## 5.6 Concluding Thoughts: A Coming Singularity?

We developed this chapter upon a number of prior ideas. First, the production of new knowledge is central to sustaining economic growth (Romer 1990, 1993). Second, the production of new ideas is fundamentally a combinatorial process (Weitzman 1998). Third, given this combinatorial process, technologies that predict what combinations of existing knowledge will yield useful new knowledge hold out the promise of improving growth prospects. Fourth, breakthroughs in AI represent a potential step change in the ability of algorithms to predict what knowledge is potentially useful to researchers and also to predict what combinations of existing knowledge will yield useful new discoveries (LeCun, Bengio, and Hinton 2015).

In a provocative recent paper, William Nordhaus (2015) explored the possibilities for a coming “economic singularity,” which he defines as “[t]he idea . . . that rapid growth in computation and artificial intelligence will cross some boundary or singularity after which economic growth will accelerate sharply as an ever-accelerating pace of improvements cascade through the economy.” Central to Nordhaus’ analysis is that rapid technological advance is occurring in a relatively small part of the economy (see also Aghion, Jones, and Jones 2018). To generate more broadly based rapid growth, the products of the new economy need to substitute for products on either the demand- or supply-side of the economy. His review of the evidence—including, critically, the relevant elasticities of substitution—leads him to conclude that a singularity through this route is highly unlikely.

However, our chapter’s analysis suggests an alternative route to an economic singularity—a broad-based alteration in the economy’s knowledge production function. Given the centrality of new knowledge to sustained growth at the technological frontier, it seems likely that if an economic singularity were to arise, it would be because of some significant change to the knowledge production function affecting a number of domains outside of information technology itself. In a world where new knowledge is the result of combining existing knowledge, AI technologies that help ease needle-in-the-haystack discovery challenges could affect growth prospects, at least along the transition path to the steady state. It does not take an impossible leap of imagination to see how new meta technologies such as AI could alter—perhaps modestly, perhaps dramatically—the knowledge production function in a way that changes the prospects for economic growth.

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# Author Index

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- Abadie, A., 531  
Ablon, L., 448  
Abrahamson, Z., 420  
Abramovitz, M., 32  
Acemoglu, D., 23n1, 43, 89, 90, 105, 127, 141, 152, 197, 198, 201, 202, 203, 203n4, 204, 204n5, 205, 206, 208, 210, 211, 212n7, 219, 220, 220n11, 223, 224, 225n14, 238, 240, 243, 271, 283, 293n3, 376n27, 376n28, 554  
Acquisti, A., 410, 416, 424, 440n2, 444, 448, 451, 457, 457n42, 459, 483n19  
Adee, S., 426  
Agarwal, A., 82n12, 83  
Aghion, P., 122, 172, 262, 262n19, 263, 265, 267, 268, 373n23, 465, 477, 479, 495  
Agrawal, A., 5, 39, 90, 97n8, 150, 161, 167, 241, 425, 464, 501  
Aguiar, M., 386n36  
Airoidi, E., 80  
Akerlof, G., 378  
Akerman, A., 7, 303  
Alexopoulos, M., 555  
Allen, R. C., 204, 209  
Alloway, T., 29  
Alon, T., 43  
Alpaydin, E., 92  
Altman, S., 325  
Alvarez-Cuadrado, F., 241n4  
Anderson, R., 406, 416  
Andrade, E. B., 592n3  
Andrews, D., 30  
Angermueller, C., 168  
Aral, S., 43  
Arntz, M., 321  
Aronoff, M., 497  
Arrow, K., 9, 43, 110, 118, 148, 364n11, 366, 412  
Arthur, B. W., 150  
Asher, S., 525  
Athey, S., 68, 425, 448, 449, 510, 514, 515, 516, 517, 519, 523, 524, 525, 527, 528, 529, 530, 531, 532, 533, 534, 536, 538  
Atkeson, A., 42n19  
Autor, D. H., 7, 23n1, 30, 89, 198, 202n3, 203, 208, 220n11, 238, 239n3, 240, 271, 309, 322, 475, 555  
Axelrod, R., 413  
Ayres, R., 201  
Azoulay, P., 475, 477  
  
Babcock, L., 592n5  
Bai, J., 532  
Baker, D., 366n14  
Baker, G., 107  
Banbura, M., 537  
Barkai, S., 271  
Barrat, J., 350  
Baslandze, S., 263, 264  
Bastani, H., 529  
Baumol, W., 38n14, 238  
Bayati, M., 529, 531, 532, 536  
Belloni, A., 93, 522  
Bengio, S., 401

- Bengio, Y., 71, 74, 75, 75n6, 149, 168, 168n6, 172  
Benzell, S. G., 90, 336  
Berg, A., 373n24  
Beron, K. J., 483  
Bertocchi, G., 430  
Bessen, J. E., 23n1, 203, 300, 413, 555  
Bhatt, M. A., 592n4  
Bickel, P. J., 522  
Binmore, K., 589, 589n1, 593  
Bjorkegren, D., 516, 519  
Blake, T., 582  
Blattberg, R. C., 598  
Blei, D. M., 507, 510, 515, 532, 533, 534  
Bloom, N., 27, 150, 223, 259n15, 268, 560  
Bolton, P., 92, 95, 95n5, 96n7, 100, 112  
Boppart, T., 241n4, 295  
Borenstein, S., 413  
Bornmann, L., 153  
Bostrom, N., 3, 286, 381, 382, 382n31  
Bottou, L., 79  
Bousquet, O., 79  
Bowen, W., 38n14  
Brandeis, L. D., 431, 459  
Brander, J. A., 473  
Brandimarte, L., 448  
Brandt, L., 471  
Bresnahan, T. F., 4, 39, 42, 116, 119, 120, 169, 176n2, 310  
Bridgman, B., 38  
Brooks, R., 124  
Broseta, B., 593n9, 594n9  
Brown, J., 314  
Brunskill, E., 528  
Brynjolfsson, E., 23, 23n1, 28n7, 30, 39, 40, 42, 43, 47, 50, 89, 119, 120, 150, 197, 201, 204, 309, 555, 557, 560, 563  
Brzeski, C., 556  
Buera, F. J., 293, 293n2  
Buffie, E. F., 373n24  
Bughin, J., 408  
Burk, I., 556  
Busch, M. L., 474, 475n13  
Byers, J. W., 577n5  
Byrne, D. M., 29, 319  
Camerer, C. F., 589, 589n1, 590, 593, 594n10, 595, 598  
Campbell, K., 450  
Cardarelli, R., 29  
Carley, M., 130, 132  
Case, A., 26  
Catalini, C., 150, 425, 448, 449, 454  
Cavusoglu, H., 450  
Cette, G., 27  
Chandler, A. D., 206  
Chapelle, O., 529  
Chapman, J. P., 599  
Chapman, L. J., 599  
Chernozhukov, V., 93, 522, 523, 527  
Chetty, R., 270  
Chevalier, J., 577n5  
Chiou, L., 428, 448  
Chong, J.-K., 593, 595  
Christie, W. G., 414  
Chui, M., 331  
Clark, C., 295  
Cockburn, I., 150  
Coey, D., 514  
Cohen, J., 555  
Cohen, L., 501  
Comin, D., 241n4, 295  
Corrigan, B., 597  
Costa-Gomes, M. A., 593, 593n9, 594n9  
Courville, A., 71, 75n6  
Cowen, T., 27, 150  
Cowgill, B., 562  
Cranor, L. F., 424, 458  
Crawford, V. P., 593, 593n9, 594n9  
Criscuolo, C., 30  
Dana, J., 599  
Danaylov, N., 253  
Dasgupta, P., 366n15  
Datta, A., 433  
Dauth, W., 556  
David, P. A., 4, 41, 42n19, 119  
Davies, R. B., 483  
Dávila, E., 354  
Dawes, R. M., 597, 598, 599, 599n15  
Dawsey, K., 29  
Deaton, A., 26, 85  
Della Vigna, S., 411  
Delli Gatti, D., 361, 362n9, 380  
De Loecker, J., 30  
Dennis, B. N., 293n2  
Dewatripoint, M., 112  
Diamond, A., 531  
Dietvorst, B. J., 426  
Dimakopoulou, M., 529  
Dimico, A., 430  
Dobson, W., 485n23  
Dogan, M., 107n9  
Doi, E., 599  
Domingos, P., 93  
Doms, M., 562

- Dorantes, C., 450  
Dorn, D., 208  
Dosi, G., 366n14  
Doudchenko, N., 531  
Dover, Y., 577n5  
Drandakis, E., 376n27  
Dubé, J.-P., 410  
Dudik, M., 528  
Duffo, E., 539  
Dunne, T., 562  
Dupuit, J., 296, 298  
Duranton, G., 480, 567  
Dwork, C., 453  
Dzamba, M., 116  
  
Eckles, D., 538  
Edwards, D. D., 598  
Edwards, J. S., 598  
Edwards, L., 294  
Edwards, W., 595  
Eeckhout, J., 30  
Egami, N., 510  
Einhorn, H. J., 598, 599  
Elkin-Koren, N., 583  
Elsby, M. W. L., 270, 329  
Engel, E., 295  
Engerman, S. L., 430  
Engstrom, R., 537  
Erlingsson, U., 453  
Ethier, W. J., 476  
Etzioni, O., 410  
Evenson, R. E., 140  
Ezrachi, A., 414  
  
Fajgelbaum, P., 480  
Farrell, J., 424  
Faure-Grimaud, A., 92, 95, 95n5, 96n7, 100, 112  
Faust, D., 597  
Fehr, E., 358n8  
Feldman, M. P., 560  
Feldstein, M., 29  
Feraud, R., 529  
Fernald, J. G., 27, 29, 32, 319  
Feurer, M., 70  
Filippas, A., 577n5  
Finklestein, A., 503  
Fleming, L., 161, 479  
Florêncio, D., 452  
Foellmi, R., 295  
Forbes, S., 108  
Ford, M., 201, 204, 301  
Forsythe, R., 590n2  
Fortunato, M., 25  
Fredriksson, P. G., 483  
Frey, C. B., 291, 321, 331, 350n1, 553, 555, 556  
Friedman, J., 93  
Frosst, N., 76n7  
Fudenberg, D., 413, 594  
Fujii, H., 465  
Fung, A., 459  
Furman, J. L., 30, 122, 140, 150, 553  
  
Gaarder, I., 7, 303  
Gabaix, X., 604  
Gaggl, P., 303  
Gal, M. S., 583  
Gal, P., 30  
Galasso, A., 495, 496, 497, 498, 501  
Gans, J., 5, 39, 90, 97n8, 171, 425, 454, 464, 550  
Garicano, L., 267  
Geanakoplos, J., 354, 368n19  
Geank, 369  
Gehring, J., 25  
Gentszkow, M., 411  
Gibbons, R., 107  
Glaeser, E. L., 516, 537, 548  
Goel, S., 516  
Goeree, J., 593  
Goh, G., 151n1, 168  
Goldberg, L. R., 597, 601n19  
Golden, J. M., 577n5  
Goldenshluger, A., 529  
Goldfarb, A., 5, 39, 90, 97n8, 148, 150, 161, 167, 425, 427, 448, 464, 482, 483, 483n19, 550, 593n8  
Goldin, C., 209, 322  
Goldman, M., 536  
Gomez-Uribe, C., 603  
Good, I. J., 238, 253  
Goodfellow, I., 66, 71, 75n6, 401  
Goolsbee, A. D., 310, 312, 314  
Gopalan, P., 510  
Gordon, R. D., 305, 310, 349  
Gordon, R. J., 27, 150, 175, 210, 223, 259n15, 264  
Graepel, T., 429  
Graetz, G., 201, 274, 319, 554  
Graff Zivin, J. S., 475, 477  
Graham, M., 459  
Green, J., 502  
Greenstein, S., 119  
Greenwald, B., 354, 364n11, 366n15, 368n19, 369, 370, 412

- Gregory, T., 321  
Griliches, Z., 116, 120, 170  
Grissen, D., 516, 519  
Groover, M., 201, 205  
Groshen, E. L., 350  
Gross, R., 451  
Grossman, G. M., 464, 476, 477, 478, 479, 480, 482  
Grove, W. M., 597  
Guerrieri, V., 293n3  
Gurun, U., 501  
Gutiérrez, G., 30  
Guvenen, F., 29  
  
Ha, Y., 599  
Hahn, J., 522  
Haile, P. A., 515  
Hainmueller, J., 531  
Hall, B. H., 132  
Hall, R. E., 47  
Hansen, C., 93, 522  
Hanson, G. H., 208  
Hanson, R., 386n36  
Harari, Y., 383  
Hardt, M., 80  
Harrell, E., 443, 444  
Hart, O., 269  
Hartford, J., 68, 75, 79n9, 526, 594  
Haskel, J., 18  
Hastie, T., 93, 526  
Hatzius, J., 29  
Haugeland, J., 69  
Hawkins, J., 93  
Hay, B., 494n2, 499  
Hazan, E., 408  
He, K., 75  
Heckman, J. J., 85, 182  
Heifels, A., 116  
Helpman, E., 169, 464, 476, 477, 478, 479, 480  
Hemous, D., 241  
Hendel, I., 412  
Henderson, R., 42, 43, 150  
Herley, C., 452  
Herrendorf, B., 204, 241n4  
Hersh, J., 537  
Hicks, J., 350, 368  
Hillis, A., 516  
Hinton, G. E., 68, 74, 76n7, 124, 125, 149, 168, 168n6, 172  
Hirschman, A., 178  
Hitt, L., 42, 43, 120  
Ho, T.-H., 592n3, 593, 595  
  
Hobijn, B., 270, 329  
Hoch, S. J., 598  
Hochreiter, S., 73, 76  
Hodas, N., 151n1, 168  
Hoffman, D., 444, 457  
Hoffman, M., 447n17  
Hofman, J. M., 510  
Hogarth, R. M., 598  
Holmes, T. J., 43  
Holmstrom, B., 112, 269  
Holt, C., 593  
Hoos, H., 575  
Hornik, K., 74, 525  
Hortaçsu, A., 43, 593n8  
Horton, J. J., 577n5  
Hotborn, T., 525  
Howitt, P., 122, 262n19, 263, 477  
Hubbard, F., 494n2, 500  
Huber, P., 494  
Hunt, N., 603  
Hutter, F., 575  
Hutter, M., 237n1  
  
Imbens, G. W., 68, 517, 522, 523, 524, 525, 529, 530, 536, 538  
Iriberry, N., 593, 594n10  
Irwin, D. A., 477  
Isçan, T. B., 293n2  
  
Jaffe, A. B., 132, 150  
Jaravel, X., 312  
Jarrell, G., 502  
Jayadev, A., 366n14  
Jean, N., 537  
Jewitt, I., 112  
Jha, S., 94, 95  
Jiang, N., 528  
Jin, G. Z., 442n4  
Joachims, T., 528  
Johnson, E. J., 589, 593, 603  
Jones, B. F., 127, 150, 155, 161, 259, 259n15, 373n23  
Jones, C. I., 46, 150, 152, 159, 160, 170n9, 171n9, 240, 252, 259n15, 373n23  
Jones, R. W., 472  
Jordan, M. I., 509, 532  
Jovanovic, B., 41  
  
Kaboski, J. P., 293, 293n2  
Kahn, L. B., 447n17  
Kahneman, D., 596, 600, 604  
Kaldor, N., 240  
Kallus, N., 528

- Kaplan, J., 3  
 Kaplow, L., 500  
 Kapur, D., 150  
 Karabarbounis, L., 270, 329  
 Karagözoğlu, E., 589  
 Katz, L. F., 7, 209, 322  
 Kehoe, P. J., 42  
 Kehrig, M., 270  
 Kendrick, J. W., 43  
 Kennan, J., 590n2  
 Kennedy, C., 376  
 Keynes, J. M., 379  
 Kislev, Y., 140  
 Kitagawa, T., 527  
 Klayman, J., 599  
 Kleinberg, J., 15, 507, 516, 518, 548, 588, 597  
 Klenow, P. J., 310, 312, 477  
 Klette, T. J., 479  
 Kleven, H. J., 270  
 Knetsch, L., 604  
 Ko, M., 450  
 Kogler, D. F., 560  
 Koh, D., 329  
 Kohno, T., 446  
 Kolb, D. A., 207  
 Kollmeyer, C., 293n2  
 Komarova, T., 538  
 Kominers, D., 501, 516  
 Kongsamut, P., 241n4, 295  
 Korinek, A., 354, 365, 366n14, 371, 373, 383, 384  
 Korolova, A., 453  
 Kortum, S. S., 259, 259n15, 479  
 Kosinski, M., 429  
 Kotlikoff, L. J., 336, 344  
 Krajbich, I., 592n6  
 Kravitz, L., 325  
 Krisiloff, M., 325  
 Krizhevsky, A., 68, 74, 125  
 Krueger, A. B., 7, 482  
 Krugman, P. R., 464, 472, 479, 480  
 Krussell, P., 265  
 Künzle, S., 527  
 Kurakin, A., 401  
 Kurakin, P. R., 464  
 Kurzweil, R., 238, 253, 253n12, 350, 373n23, 381, 382  
 Kuznets, S., 205, 206  
 Lada, A., 540  
 Laffont, J.-J., 514  
 LaGarda, G., 336  
 Laibson, D., 606  
 Lambrecht, A., 425, 426  
 Lancaster, K., 362  
 Landes, D., 206  
 Lane, J., 554, 562  
 Langford, J., 528  
 Lanier, J., 84  
 Lashkari, D., 241n4, 295  
 Lawrence, R. Z., 294  
 LeCun, Y., 75, 149, 168, 168n6, 172  
 Lederman, M., 108, 550  
 Legg, S., 237n1  
 Leung, M. K. K., 121  
 Levin, J., 514, 515  
 Levine, D. K., 43  
 Levine, S., 38  
 Levinthal, D., 161  
 Levitt, S. D., 43  
 Levy, F., 37, 202n3, 238, 239n3  
 Lewis, E., 562  
 Lewis, G., 526, 527  
 Lewis, M., 596  
 Lewis, R. A., 541n2  
 Lewis, W. A., 294  
 Leyton-Brown, K., 569, 575, 594  
 Li, D., 447n17, 529  
 Li, L., 528, 529, 580, 581  
 Liang, A., 588, 594  
 Lim, K., 465, 479  
 Lindor, R., 494  
 Lipsey, R., 362  
 List, J. A., 43  
 Litan, R. E., 441n2, 494  
 Liu, Y., 38  
 Long, N., 241n4  
 Lovallo, D., 600  
 Lowenstein, G., 448, 592n5  
 Lu, Y., 529  
 Luo, H., 495, 496, 497, 498, 501  
 Lusinyan, L., 29  
 Lusted, L. B., 94  
 Malthus, T. R., 384  
 Mamoshina, P., 168n7  
 Managi, S., 465  
 Mandel, M., 555  
 Manning, A., 379  
 Mantoux, P., 200, 203  
 Manuelli, R. E., 205, 243n6  
 Manyika, J., 331  
 Marchant, G., 494n2  
 Marco, A., 130, 132  
 Markov, J., 93



- Markusen, J. R., 476  
Marthews, A., 425  
Marx, M., 479  
Massey, C., 426  
Masterov, D. V., 578, 579  
Matsuyama, K., 294, 295  
Mayer, U. F., 578, 579  
Mayer, W., 471  
Mayzlin, D., 577n5  
McAfee, A., 23, 23n1, 30, 40, 50, 89, 150, 201, 204, 309, 555  
McCall, J. J., 582  
McClelland, J. L., 602  
McDonald, A. M., 424, 458  
McElheran, K., 560  
McFadden, D., 85, 514  
Mcguckin, R. H., 562  
McHale, J., 150, 241  
McLaren, J., 469  
McSweeney, T., 583  
Meade, J. E., 362  
Meadows, M., 420  
Meehl, P. E., 596, 597  
Meltz, M. J., 488  
Mestieri, M., 241n4, 295  
Mian, A., 208  
Michaels, G., 201, 274, 319, 554  
Mikolov, T., 76  
Milgrom, P. R., 43, 111, 567, 569, 574, 577  
Miller, A., 428, 429, 448, 483  
Miller, S. M., 201  
Milliment, D. L., 483  
Minsky, M., 28, 208  
Miremadi, M., 331  
Mishel, L., 322  
Misra, S., 410  
Mitchell, T., 39, 557, 563  
Mnih, V., 84  
Mobius, M. M., 510  
Mogstad, M., 7, 303  
Mojon, B., 27  
Mokyr, J., 29, 121, 150, 175, 201, 206, 209  
Monro, S., 78  
Moore, G. E., 384n35, 498  
Moore, M., 496  
Morris, D. Z., 37  
Mortensen, D. T., 379, 582  
Muellbauer, J., 85  
Mullainathan, S., 169n8, 511, 512, 518, 588  
Murdoch, J. C., 483  
Murnane, R. J., 202n3, 238, 239n3  
Murphy, K., 107  
Murray, C., 325  
Murray, F., 141  
Mussa, M. L., 471  
Mutz, R., 153  
Myers, A., 130  
Myerson, R. B., 568  
Naecker, J., 592  
Naik, N., 516, 537  
Nakamura, L., 29  
Nave, G., 590  
Neal, R. M., 74  
Neelin, J., 589n1  
Neiman, B., 270, 329  
Nekipelov, D., 538  
Nelson, P., 581  
Nelson, R., 118, 161  
Newbery, D., 362  
Newell, A., 123  
Newhouse, D., 537  
Ng, A., 93, 509, 532  
Ng, S., 532  
Ngai, L. R., 241n4, 294  
Nickell, S., 293n2  
Nielsen, M., 152, 161  
Nilsson, N., 122, 207, 208  
Nordhaus, W. D., 28, 152, 172, 238  
North, D. C., 577  
Nosko, C., 577n5, 582  
O'Dea, B., 583  
Odlyzko, A., 441n2  
Oettle, A., 241  
Olmstead, A. L., 204, 205, 206  
Olsen, M., 241  
O'Mahony, S., 141  
O'Neil, C., 433  
O'Reilly, B., 499  
Orlikowski, W. J., 43  
Orszag, P., 30  
Osborne, M. A., 291, 321, 331, 350n1, 553, 555, 556  
Osindero, S., 74  
Oskamp, S., 601  
Ossard, H., 514  
Östling, R., 593n8  
Ostrovsky, M., 568  
Pajarinen, M., 556  
Pál, J., 510  
Palfrey, T., 593  
Parchomovsky, G., 494

- Pate, R. H., 420  
 Pelzman, S., 502  
 Peretto, P. F., 241  
 Peterson, N., 599  
 Peysakhovich, A., 540, 592  
 Phelps, E., 376n27  
 Philippon, T., 30  
 Pierce, D. G., 413  
 Pihur, V., 453  
 Piketty, T., 360  
 Pissarides, C. A., 241n4, 294, 379  
 Polemarchakis, H., 354, 368n19, 369  
 Polinsky, M., 494n2  
 Porter, M. E., 481, 494  
 Poschke, M., 241n4  
 Posner, R. A., 439  
 Prantl, S., 263  
 Pratt, G. A., 40  
 Proserpio, D., 577n5  
 Puga, D., 480  
  
 Raghaven, M., 518  
 Ramaswamy, R., 291, 293n2  
 Ramlogan, R., 480  
 Rao, J. M., 516, 536, 541n2  
 Rasmussen, W. D., 200, 203, 205n6, 206  
 Rauch, J. E., 469  
 Rebelo, S., 241n4, 295  
 Recht, B., 80  
 Redding, S., 293n2  
 Reinsdorf, M. B., 29  
 Rennie, J., 80  
 Restrepo, P., 23n1, 43, 90, 105, 127, 152, 197,  
     201, 202, 203, 203n4, 204, 204n5, 206,  
     208, 210, 211, 212n7, 219, 220, 220n11,  
     223, 224, 225n14, 238, 240, 241, 243,  
     271, 283, 376n27, 379, 554  
 Rhode, P. W., 204, 205, 206  
 Rhodes, E., 325  
 Rivera-Batiz, L. A., 477, 478  
 Rivkin, J., 161  
 Robbins, H., 78  
 Roberts, J., 43, 111  
 Robinson, P. M., 524, 527  
 Rock, D., 557  
 Rodrik, D., 293  
 Roesner, F., 446  
 Rogerson, R., 204, 241n4  
 Romanosky, S., 444, 450, 457, 457n42  
 Romer, P. M., 46, 122, 149, 153, 155n2, 159,  
     169, 171, 171n9, 172, 255, 477, 478  
 Rosenberg, N., 150, 169  
  
 Rosenblatt, F., 73, 124  
 Rosenfeld, J., 322  
 Rossi-Hansberg, E., 476  
 Roth, A. E., 539, 567, 584, 589  
 Rousseau, P. L., 41  
 Rouvinen, P., 556  
 Rowthorn, R., 291, 293n2  
 Rubin, D. B., 517, 522, 527, 529  
 Rubinstein, A., 427  
 Ruffin, R. J., 472  
 Ruiz, F. J., 515, 533, 534  
 Rumelhart, D. E., 73, 77, 124, 602  
  
 Sabour, S., 76n7  
 Sachs, J. D., 336, 344  
 Saez, E., 270, 360  
 Şahin, E., 270, 329  
 Salakhutdinov, R. R., 125  
 Salomons, A., 23n1, 309, 555  
 Samuelson, P., 376  
 Santaaulalia-Llopi, R., 329  
 Saon, G., 25  
 Sawyer, J., 597  
 Saxenian, A. L., 4, 478  
 Schierholz, H., 322  
 Schmidhuber, J., 73, 76  
 Schmidt, K. M., 358n8  
 Schmitt, J., 322, 379  
 Schmitz, J. A., 43  
 Schmucki, R., 497  
 Schultz, P. H., 414  
 Schumpeter, J., 148  
 Schwartz, M., 568  
 Scotchmer, S., 121, 496, 502  
 Scott, S. L., 528  
 Seater, J. J., 241  
 Segal, I., 414, 569, 574  
 Seira, E., 514  
 Seshadri, A., 205, 243n6  
 Shah, A. K., 517  
 Shaked, A., 589n1  
 Shavell, S., 494n2  
 Shaw, J. C., 123  
 Shiller, B. R., 410  
 Shroff, R., 516  
 Silver, D., 63, 66, 453  
 Simcoe, T., 487  
 Simmons, J. P., 426  
 Simon, H. A., 107, 123, 207–8  
 Sims, C., 113  
 Simsek, A., 362n10  
 Singer, Y., 80

- Slovic, P., 596  
Smith, A., 590  
Smith, M. D., 43  
Smith, N., 29  
Sokoloff, K. L., 430  
Solomonoff, R. J., 253n12  
Solove, D., 447, 455  
Soloveichik, R., 29  
Solow, R. M., 24, 46, 350  
Somanchi, S., 444  
Song, J., 30  
Sonnenschein, H., 589n1  
Sopher, B., 590n2  
Sorensen, O., 161  
Spencer, B. J., 473  
Spezio, M., 594n10  
Spiegel, M., 589n1  
Spiegel, Y., 412  
Spier, K., 494, 499, 502  
Spiess, J., 169n8, 511, 512  
Spindler, M., 522  
Srivastava, N., 80  
Stahl, D. O., 593  
Stantcheva, S., 360  
Stein, A., 494  
Stern, A., 325  
Stern, S., 122, 141  
Stevenson, B., 194n5  
Stigler, G. J., 439, 582  
Stiglitz, J. E., 30n9, 354, 360, 362, 364,  
364n11, 366n14, 366n15, 368n19, 369,  
370, 370n21, 371, 373, 376n27, 376n28,  
378, 412  
Stillwell, D., 429  
Stinchcombe, M., 74  
Stivers, A., 442n4  
Stole, L., 268  
Strehl, A., 527  
Streitwieser, M. L., 562  
Strotz, R. H., 427  
Stucke, M. E., 414  
Stutzman, F., 451  
Sufi, A., 208  
Summers, L. H., 175  
Sutskever, I., 68, 74, 125  
Sutton, J., 467, 589n1  
Swaffield, J., 293n2  
Swaminathan, A., 528  
Sweeney, L., 433  
Swire, P. P., 441n2  
Syverson, C., 23, 29, 43, 210, 319, 320  
Taddy, M., 83, 526, 527  
Tadelis, S., 107, 577n5, 578, 579, 580, 581,  
582  
Tang, J., 453  
Taylor, C. R., 416, 424, 441n2, 448, 459,  
483n19  
Tegmark, M., 382, 384n34  
Teh, Y.-W., 74  
Telang, R., 444, 450, 457, 457n42  
Teodoridis, F., 150, 161  
Tetenov, A., 527  
Thaler, R., 604  
Thomas, K., 443  
Thomas, P., 528  
Thompson, W. R., 82  
Thrnton, B., 598  
Tibshirani, R., 93, 525, 527  
Tirole, J., 106, 112, 264, 268, 269  
Topol, E. J., 94, 95  
Tory, J., 485n23  
Toulis, P., 80  
Trajtenberg, M., 4, 39, 116, 119, 132, 150,  
169, 176n2  
Trefler, D., 465, 467, 479, 485n23  
Troske, K. R., 562  
Tschantz, M. C., 433  
Tucker, C. E., 148, 425, 426, 427, 428, 429,  
448, 449, 482, 483, 483n19  
Turing, A. M., 123, 385  
Tuzel, S., 210  
Tversky, A., 596  
Ugander, J., 538  
Uyarra, E., 480  
Vadlamannati, K. C., 483  
Valentinyi, Á., 204, 241n4  
Van der Laan, M. J., 522, 527  
Van Seijen, H., 62, 84  
Varian, H. R., 93, 310, 410, 413, 424, 425,  
440, 511  
Venables, A. J., 480  
Vesteger, M., 420  
Vickrey, W., 567  
Vijverberg, W. P. M., 483  
Vincent, N., 270  
Vines, P., 446  
Vinge, V., 238, 253, 253n12, 373n23  
Viscusi, K., 496, 498  
Vishnu, A., 151n1, 168  
Von Hippel, E., 499

- Von Weizacker, C. C., 376  
 Von Winterfeldt, D., 595  
 Vuong, Q., 514
- Wager, S., 523, 525, 527, 528  
 Wagman, L., 416, 424, 441n2, 448, 459, 483n19  
 Wallach, I., 116  
 Wan, M., 534  
 Wang, J., 475, 477, 594n10  
 Warren, S. D., 431, 459  
 Waseem, M., 270  
 Wattal, S., 450  
 Weil, D., 459  
 Weingast, B. R., 577  
 Weiss, A., 354  
 Weitzman, M., 149, 151, 157, 171, 171n9, 172, 241  
 Western, B., 322  
 Westlake, S., 18  
 Whinston, M. D., 148  
 White, H., 74, 511  
 Williams, H., 122, 364n11  
 Williams, R., 124  
 Wilson, P. W., 593  
 Winter, S., 161  
 Wolfers, J., 195n5  
 Wooldridge, J. M., 522  
 Wright, G., 42n19  
 Wright, G. C., 303
- Wright, J. R., 594  
 Wu, L., 43
- Xiao, M., 593n8  
 Xie, D., 241n4, 295  
 Xu, H., 577
- Yakovlev, E., 538  
 Yang, S., 42, 47  
 Yellen, J., 378  
 Yeomans, M., 517  
 Yildirim, P., 107n9  
 Yu, M., 465, 479  
 Yudkowsky, E., 253n12
- Zanna, L.-F., 373n24  
 Zeevi, A., 529  
 Zeileis, A., 525  
 Zeira, J., 152, 198, 212n7, 238, 239, 241  
 Zervas, G., 577n5  
 Zhang, M. B., 210  
 Zheng, Y., 329  
 Zhou, D., 529, 581  
 Zhou, X., 580  
 Zhu, X., 471  
 Zierahn, U., 321  
 Zubizarreta, J. R., 523  
 Zweimüller, J., 295  
 Zwiebel, J., 268



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# Subject Index

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Note: Page numbers followed by “f” or “t” refer to figures or tables, respectively.

adoption, technological: implications of  
speed of, for job market and inequality,  
310–12

adversarial artificial intelligence, 401

aggregate productivity statistics, technolo-  
gies and, 26–28

AI. *See* artificial intelligence (AI)

AlphaGo (Google), 63

Amazon Go concept, 67

applied artificial intelligence, 208

artificial intelligence (AI), 1; and automa-  
tion of production, 239–50; as basis  
for learning, 120–21; benefit of more,  
318–20; bibliometric data on evolution  
of, 128–32; capital shares and, 270–74,  
272–73f; in context, 84–85; defined,  
3–4, 62–67, 93, 122, 237, 468; econo-  
mies of scale from data and, 468–69;  
economies of scale from overhead  
of developing AI capabilities, 469–  
70; evolution of, 122–25; expected  
productivity effects of, 45–46; firm  
organization and, 264–70; future of  
research on economics of, 17; as general  
purpose technology, 4–7, 39–41; in idea  
production function, 250–52; impact  
of, on innovation, 125–28; impact of  
long-term decline in labor force partici-  
pation rate and, 323–25; implications  
of, 349–53; income distribution and,

351; inequality and, 320–23; internal  
agreements and, 463; international  
macroeconomics and, 488; knowledge  
externalities and, 470–71; likely produc-  
tivity effects of, and acceleration of, 45–  
46; longer-term prospects of, 381–86;  
market structure and, 262–63; as “next  
big thing,” 175; political economy of,  
11, 394–95; prediction costs and, 92–93;  
privacy and, 425–26; privacy concerns  
and, 423–24; for promoting trust in  
online marketplaces, 576–81; recent  
approach to, 93; for reducing search  
frictions, 581–83; return of Malthus  
and, 381–86; revolution, international  
effects of, 393–94; in Schumpeterian  
model with creative destruction, 276–  
79; sectoral reallocation and, 263–64;  
statistics on, 465–66, 466t; studies on  
economic effect of, 556–58; theory of  
privacy in economics and, 424–26; as  
tool, 16–17; world’s largest companies  
and exposure to, 465–67, 467t. *See also*  
machine learning (ML)

artificial intelligence capital, measuring,  
46–50

artificial intelligence–general purpose tech-  
nology (GPT) era: education strategies  
for, 179–82; human-enhancing innova-  
tions vs. human-replacing innovations

- artificial intelligence—general purpose technology (GPT) era (*continued*)  
 for, 184–85; professionalization of  
 personal services strategies for, 182–84;  
 top skills required for employment in,  
 180–81, 181t
- artificial intelligence revolution, inter-  
 national effects of, 393–94
- Atomwise, case of, 115–16, 120, 154
- automatic teller machines (ATMs), security  
 policy and, 416
- automation, 3–4, 105–6; basic model, 336–  
 41; Baumol's cost disease and, 241–50;  
 to date, and capital shares, 270–74;  
 decline in labor share and, 329–31;  
 deepening of, 198, 204–5, 216–17; eco-  
 nomic adjustment and, 208–9; employ-  
 ment and, 190–91; excessive, 224–26;  
 model of, 211–14; of production, and  
 artificial intelligence, 239–50; produc-  
 tivity and, 210–11; sector of economy  
 affected by, 330–33; studies on employ-  
 ment on, 555–58; wages and, 200–211;  
 winners, 190; work and, 200–211; Zeira  
 model of growth and, 239–41
- average treatment effects, 522–24
- bandits (algorithms), problem of, 528–29
- Baumol's cost disease. *See* cost disease,  
 Baumol's
- BenchSci search technology, 153
- buy/make decisions (firm boundaries),  
 107–8
- capital accumulation, 198, 204–5, 216
- capital shares, and automation to date,  
 270–74
- causal inference, new literature on, 519–34
- Children's Online Privacy Protection Act of  
 1998 (COPPA), 454
- cloud-computing facilities, 402–3
- cluster policies, 480–81
- clusters, regional, theory of, 479
- CNNs (convolutional neural networks), 75–  
 76, 75n6
- collusion, strategies for facilitating, 413–14
- combinatorial-based knowledge production  
 function, 154–61; potential uses of new,  
 170–71; with team production, 161–67
- Communications Act (1986), 456
- competition policy, innovations and, 141–43
- complexity, 103–4
- consumer attitude, 448–49
- consumer privacy: challenging issues in,  
 457–59; consumer attitude and, 448–49;  
 consumer risk and, 443–48; data risk  
 and, 442–43; nature of problem of, 442;  
 policy landscape in United States, 454–  
 57; supply side actions and, 450–54.  
*See also* privacy
- consumer surplus, 11; distribution of,  
 391–93
- contracting, 106–7
- convolutional neural networks (CNNs),  
 75–76, 75n6
- cooperation, evolution of, 414
- cost disease, Baumol's, 8–9, 238–39; auto-  
 mation and, 241–50
- creative destruction, 260–61
- data, 61; acquisition methods, 403–4; de-  
 creasing marginal returns of, 406, 407f;  
 economics of, 14; importance of, 13–  
 14; important characteristics of, 404–6;  
 localization rules, trade policies and,  
 485–86; persistence of predictive power  
 of, 427–28; privileged access to govern-  
 ment, trade policies and, 486–87;  
 types of, and generation of spillovers,  
 431–34
- data access, 405–6
- data generation, as pillar of artificial intel-  
 ligence, 62f, 65–66
- data ownership, 405–6
- data persistence, 426–27; predictive power  
 and, 427–28
- data pipeline, 402
- data pyramid, 404, 405f
- data repurposing, 428–31
- data security: challenging issues in, 457–  
 59; policy landscape in United States,  
 454–57
- data spillovers, 431–34
- data warehouses, 402–3
- decision-making, baseline model for, 95–  
 103; complexity and, 103–8
- deepening of automation, 198, 204–5,  
 216–17
- Deep Genomics, 154
- deep learning, 3, 71–77, 400; as general pur-  
 pose invention in method of invention,  
 139–43; as general purpose technology,  
 133–39; as new discovery tool, 167–69;  
 patent systems and, 142

- deep learning networks, 94  
 deep learning techniques, 25  
 deep neural networks (DNNs), 25–26, 61,  
     63; structure in, 76–77  
 demand, importance of, 301–2  
 destruction, creative, 260–61  
 difference-in-difference models, 530–31  
 digital information, 334–35  
 direct network effects, 412  
 displacement effect, 8, 198, 208, 214  
 DNNs. *See* deep neural networks (DNNs)  
 domain structure, as pillar of artificial intel-  
     ligence, 62f, 63–65  
 double machine learning, 523–24  
  
 economic growth: artificial intelligence and,  
     262–70; prospects for technology-  
     driven, 149–53; Zeira model of auto-  
     mation and, 239–41. *See also* growth  
 economics, impact of machine learning on  
     practice of, 15–16  
 education, factory model of, 180  
 Electronic Communications Privacy Act of  
     1986: (ECPA), 456  
 employment: automation and, 190–91;  
     levels of, and new technologies, 220–21;  
     long-run vs. short run, 192–94; studies  
     on automation and, 555–57; work out-  
     side of, 194–95  
 evolution of cooperation, 414  
  
 factory model of education, 180  
 Federal Trade Commission (FTC), 454–55  
 firm boundaries (make/buy decisions),  
     107–8  
 firm-level data: need for, 558–59; strategies  
     for collecting, 561–62  
 firm-level research questions, 560–61  
 firms: artificial intelligence and, 262–70;  
     impact of machine learning on, 12  
  
 general purpose machine learning (GPML),  
     67–71  
 general purpose technology (GPT), 2, 65,  
     119–20, 169–70; artificial intelligence  
     as, 4–7, 39–41; deep learning as, 133–  
     39; viewing today's Solow paradox  
     through previous history of, 44–45  
 generative adversarial networks (GANs),  
     66–67  
 GPML (general purpose machine learning),  
     67–71  
  
 GPT. *See* general purpose technology (GPT)  
 Gramm-Leach-Bliley Act (GLBA), 454  
 growth: impact of artificial intelligence on,  
     7–9. *See also* economic growth  
  
 Health Insurance Portability and Account-  
     ability Act of 1996 (HIPAA), 454  
 HEI (human-enhancing innovations),  
     184–85  
 heterogeneous treatment effects, 524–28  
 hierarchical Poisson factorization, 510  
 HIPAA. *See* Health Insurance Portabil-  
     ity and Accountability Act of 1996  
     (HIPAA)  
 HRI (human-replacing innovations), 184–85  
 human-enhancing innovations (HEI), 184–85  
 human-replacing innovations (HRI), 184–85  
  
 idea production function, artificial intelli-  
     gence in, 250–52  
 implementation/restructuring lags, as expla-  
     nation for Solow paradox, 31–36  
 incentive auctions, machine learning and,  
     569–76  
 income, artificial intelligence and, 189–90  
 income distribution: artificial intelligence  
     and, 351; impact of AI on, 11  
 income inequality: artificial intelligence and,  
     320–23; impact of AI on, 7–8, 11–12;  
     speed of technological adoption and,  
     310–12  
 income redistribution, political economy of,  
     394–95  
 indirect network effects, 412  
 industrial regulation, trade policies and, 487  
 inequality. *See* income inequality  
 information technology (IT), 24  
 innovation, 115–18; competition policy and,  
     141–43; early stage, 121–22; impact  
     of artificial intelligence on, 125–28;  
     institutions and, 141–43; management  
     and organization of, 140–41; product  
     liability and, 494  
 institutions, innovations and, 141–43  
 intelligence-assisting innovation (IA),  
     350–51  
 International Federation of Robotics  
     (IFR), 16  
 international macroeconomics, artificial  
     intelligence and, 488  
 international trade, economics of data  
     and, 14



- invention of a method of inventing (IMI), 120–21, 124
- inverted-U pattern, 293; simple model of, 297–301
- JDM (judgment and decision-making) research, 596–98
- job displacement, 310–12
- job losses, 291
- job markets, speed of technological adoption and, 310–12
- jobs, impact of artificial intelligence on, 7–8, 9–11
- judgment: in absence of prediction, 96–101; as complements/substitutes to prediction, 102–3; creating role for, 91; prediction and, 91–92
- judgment and decision-making (JDM) research, 596–98
- knowledge creation, 477–79
- knowledge externalities, and artificial intelligence, 470–71
- knowledge spillovers, 479
- labor: comparative advantage of, and new tasks, 217–18; model of demand for, 211–14
- labor demand, technology and, 214–21
- labor productivity growth, technologies and, 26–28
- learning by doing, 412–13
- liability, innovation and, 494; empirical evidence on, 496–98; theoretical model of, 494–96
- liability, tort, development of artificial intelligence technologies and, 498–502
- machine learning (ML), 3, 24–25; applications of, 401–2; defined, 509–10; double, 523–24; early use cases of, 510–15; for finding behavioral variables, 587–96; general purpose, 67–71; human prediction as imperfect, 496–603; impact of, 12–13, 15–17, 507–9; incentive auctions and, 569–76; new literature on, 519–34; overview, 399–406; predictions about impact of on economics, 534–42; regulation and, 12–15; supervised, 511–12; unsupervised, 510–11; vertical integration and, 408–9. *See also* artificial intelligence (AI)
- machine learning–provision industries, 414–15
- machine learning–using industries, 408f; boundaries and, 409–10; firm size and, 409–10; price differentiation and, 410–11; pricing and, 410; returns to scale and, 411–14; structure of, 406–8
- macroeconomics, international, artificial intelligence and, 488
- make/buy decisions (firm boundaries), 107–8
- Maluuba, 62–63
- market design, introduction to, 567–69
- massive open online courses (MOOCs), 181
- matrix completion problem, 531–32
- matrix factorization, 51, 511
- meta technologies, 153
- ML. *See* machine learning (ML)
- model averaging, 511
- MOOCs (massive open online courses), 181
- neural networks, 72–74, 123, 124–25, 510, 511
- new economic geography (NEG), 479–80
- online marketplaces, using artificial intelligence to promote trust in, 576–81
- optical lenses, invention of, 121
- optimism, sources of technological, 24–26
- Pareto improvement, 363
- patent systems, deep learning and, 142
- Pen Register Act (1986), 456
- policy analysis, using methods of prediction for, 516–19
- political economy: of artificial intelligence, 11; of income redistribution, 394–95; of technological disruptions, 176–79
- prediction: in absence of judgment, 101–2; artificial intelligence as tool for, 16–17; as complements/substitutes to judgment, 102–3; costs of, and AI, 92–93; judgment and, 91–92; using methods of, in policy analysis, 516–19
- premature deindustrialization, 393–94
- price discrimination, artificial intelligence and, 604
- principal components analysis, 74, 92, 510
- privacy, 13–14; artificial intelligence and,

- 425–26; current models of economics and, 424–25; data spillovers and, 431.  
*See also* consumer privacy
- privacy policy, 416–17
- privacy regulation, trade policies and, 482–85
- privileged access to government data, trade policies and, 486–87
- production, automation of, and artificial intelligence, 239–50
- productivity: automation and, 210–11; missing growth of, and new technologies, 223–26
- productivity effects, 198, 203–4, 214–16
- productivity growth: low current, reasons why it is consistent with future technological growth, 41–44; rates of, technologies and, 26–28; slow, and future productivity growth, 31–36
- productivity optimism, technology-driven case for, 36–39
- radiology, case of, 94–95
- random forest, 511
- R&D. *See* research and development (R&D)
- recommender systems, 603
- regional clusters, theory of, 479
- regression trees, 511
- regularization on norm of matrix, 510
- regularized regression, 511
- regulation, 12–15; machine learning and, 12–15
- reinforcement learning, 25, 66, 81–84, 400–401
- reinstatement effect, 8, 198, 206
- research and development (R&D), 336; productivity, effects of rise in, 341–43
- research tools, economics of new, 118–22
- robotics, 123–24; tort law and, 493–94.  
*See also* robots
- robots, studies on, 554–55. *See also* robotics
- Romer/Jones knowledge production function, 151–52
- scale, economies of, and artificial intelligence, 470
- Schumpeterian model with artificial intelligence, 276–79
- scientific discovery, rate of, 6
- scientists, role of, 472–73; superstar, 474–76
- scope, economies of, and artificial intelligence, 470
- search frictions, artificial intelligence for reducing, 581–83
- security policy, 416
- singularities, 253–61; examples of technological, 254–58; objections to, 258–61
- skills: mismatch of technologies and, 221–23; technologies and, 209
- Solow paradox, 24; potential explanations for, 28–31
- source code, trade policies and, 487–88
- spectrum reallocation, 569–76, 572f
- spillovers, data, 431
- spreadsheet software, invention and impact of, 90
- stochastic gradient descent optimization, 77–81
- strategic trade policy, 473–74
- structural change, 293–96
- structural models, 532–34
- superstar scientists, role of, 474–76
- supervised machine learning, 511; methods for, 511–12
- supplementary analysis, 530
- support vector machines, 511
- symbolic processing hypothesis, 123
- symbolic systems, 123
- tasks, new, 205–7; comparative advantage of labor and, 217–18; creation of, 198; model of, 211–14
- technological changes: factor-biased, 376–77; and levels of employment, 220–21; types of, 212–13
- technological disruptions, political economy of, 176–79
- technological growth, reasons why it is consistent with low current productivity growth, 41–44
- technological optimism, sources of, 24–26
- technological progress: channels of inequality and, 365–70; determining scenarios that best describe economy, 363–64; endogenous, 364–65; first-best scenario, 353–56; imperfect markets scenario, 361–62; perfect markets but costly redistribution scenario, 358–61; perfect markets ex post and no costs of redistribution scenario, 356–58; welfare and, 353–65; worker-replacing, redistribution and, 370–77
- technological singularities, examples of, 254–58

- technological unemployment, 377–81
- technologies: future progress of, and low current productivity growth, 41–44;
  - labor demand and, 214–21; mismatch of skills and, 221–23; skills and, 209
- technology-driven economic growth, prospects for, 149–53
- tort law, robotics and, 493
- tort liability, 14
- total factor productivity growth, 32
- trade models, basic, 476–77
- trade policies: data localization rules and, 485–86; industrial and strategic, case for, 471–81; industrial regulation and, 487; privacy regulation and, 482–85; privileged access to government data and, 486–87; role of university-related talent, 472–76; source code and, 487–88; strategic, 473–74
- UBI. *See* universal basic income (UBI)
- unemployment, technological, 377–81
- universal basic income (UBI), 312–14; cost of replacing current safety net with, 325–26
- unsupervised machine learning, 510–11
- USA Patriot Act (2001), 456
- vertical integration, machine learning and, 408–9
- vertical research spillovers, 122
- wages, automation and, 200–211
- welfare, technological progress and, 353–65
- work, automation and, 200–211
- worker-replacing technological progress:
  - dynamic implications of, 373–74; redistributing innovators' surplus and, 374–76; redistribution and, 370–77; static pecuniary externalities of, 371–72
- Zeira model of automation and growth, 239–41
- “zero-shot” learning systems, 66