

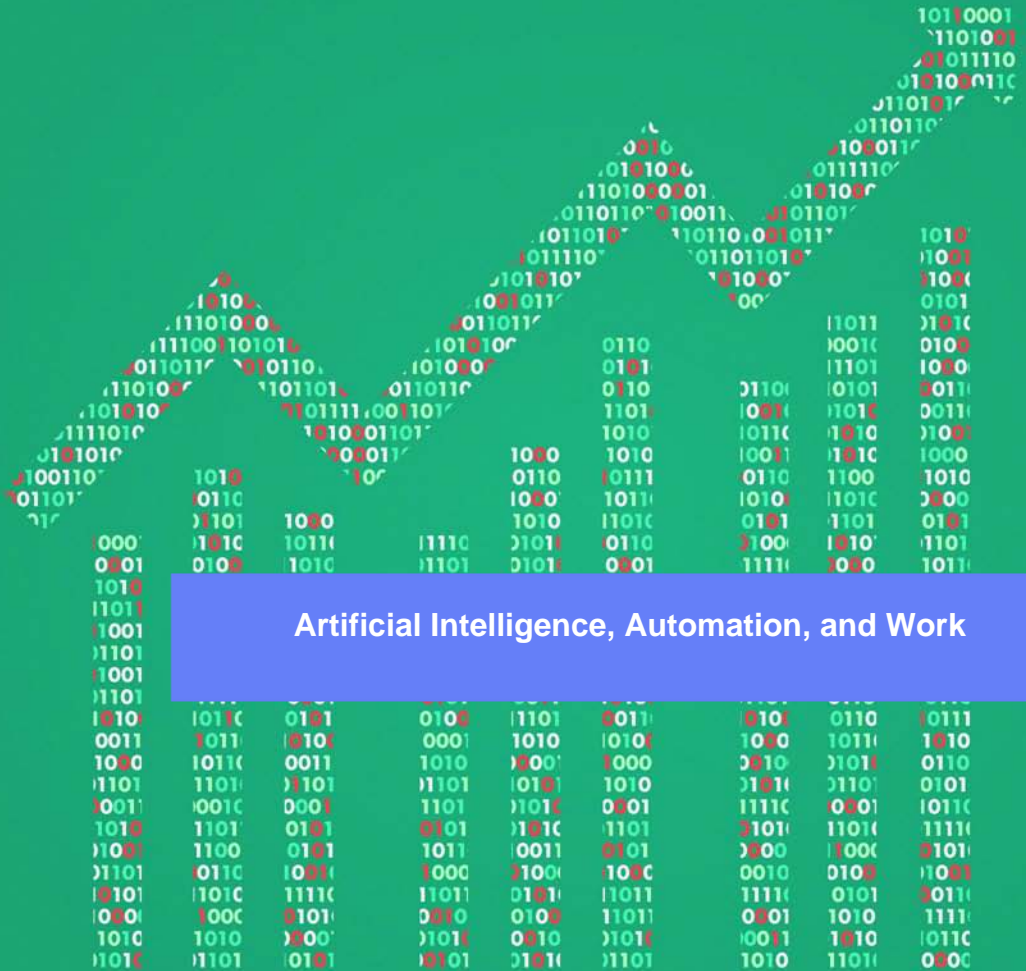


National
Bureau of
Economic
Research

THE ECONOMICS OF ARTIFICIAL INTELLIGENCE

An Agenda

Edited by Ajay Agrawal,
Joshua Gans, and Avi Goldfarb

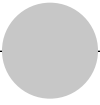


Artificial Intelligence, Automation, and Work

The Economics of Artificial Intelligence



**National Bureau of
Economic Research
Conference Report**



The Economics of Artificial Intelligence: An Agenda

Edited by

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

The University of Chicago Press

Chicago and London

The University of Chicago Press, Chicago 60637
The University of Chicago Press, Ltd., London
© 2019 by the National Bureau of Economic Research, Inc.
All rights reserved. No part of this book may be used or reproduced
in any manner whatsoever without written permission, except in the
case of brief quotations in critical articles and reviews. For more
information, contact the University of Chicago Press, 1427 E. 60th St.,
Chicago, IL 60637.
Published 2019
Printed in the United States of America

28 27 26 25 24 23 22 21 20 19 1 2 3 4 5

ISBN-13: 978-0-226-61333-8 (cloth)
ISBN-13: 978-0-226-61347-5 (e-book)
DOI: <https://doi.org/10.7208/chicago/9780226613475.001.0001>

Library of Congress Cataloging-in-Publication Data

Names: Agrawal, Ajay, editor. | Gans, Joshua, 1968– editor. | Goldfarb, Avi, editor.

Title: The economics of artificial intelligence : an agenda / Ajay Agrawal, Joshua Gans, and Avi Goldfarb, editors.

Other titles: National Bureau of Economic Research conference report.

Description: Chicago ; London : The University of Chicago Press, 2019. | Series: National Bureau of Economic Research conference report | Includes bibliographical references and index.

Identifiers: LCCN 2018037552 | ISBN 9780226613338 (cloth : alk. paper) | ISBN 9780226613475 (ebook)

Subjects: LCSH: Artificial intelligence—Economic aspects.

Classification: LCC TA347.A78 E365 2019 | DDC 338.4/70063—dc23

LC record available at <https://lccn.loc.gov/2018037552>

© This paper meets the requirements of ANSI/NISO Z39.48-1992 (Permanence of Paper).

National Bureau of Economic Research

Officers

Karen N. Horn, <i>chair</i>	Kelly Horak, <i>controller and assistant corporate secretary</i>
John Lipsky, <i>vice chair</i>	Alterra Milone, <i>corporate secretary</i>
James M. Poterba, <i>president and chief executive officer</i>	Denis Healy, <i>assistant corporate secretary</i>
Robert Mednick, <i>treasurer</i>	

Directors at Large

Peter C. Aldrich	Diana Farrell	Michael H. Moskow
Elizabeth E. Bailey	Jacob A. Frenkel	Alicia H. Munnell
John H. Biggs	Robert S. Hamada	Robert T. Parry
John S. Clarkeson	Peter Blair Henry	James M. Poterba
Kathleen B. Cooper	Karen N. Horn	John S. Reed
Charles H. Dallara	Lisa Jordan	Marina v. N. Whitman
George C. Eads	John Lipsky	Martin B. Zimmerman
Jessica P. Einhorn	Laurence H. Meyer	
Mohamed El-Erian	Karen Mills	

Directors by University Appointment

Timothy Bresnahan, <i>Stanford</i>	George Mailath, <i>Pennsylvania</i>
Pierre-André Chiappori, <i>Columbia</i>	Marjorie B. McElroy, <i>Duke</i>
Alan V. Deardorff, <i>Michigan</i>	Joel Mokyr, <i>Northwestern</i>
Edward Foster, <i>Minnesota</i>	Cecilia Rouse, <i>Princeton</i>
John P. Gould, <i>Chicago</i>	Richard L. Schmalensee, <i>Massachusetts Institute of Technology</i>
Mark Grinblatt, <i>California, Los Angeles</i>	Ingo Walter, <i>New York</i>
Bruce Hansen, <i>Wisconsin–Madison</i>	David B. Yoffie, <i>Harvard</i>
Benjamin Hermalin, <i>California, Berkeley</i>	
Samuel Kortum, <i>Yale</i>	

Directors by Appointment of Other Organizations

Jean-Paul Chavas, <i>Agricultural and Applied Economics Association</i>	Robert Mednick, <i>American Institute of Certified Public Accountants</i>
Martin J. Gruber, <i>American Finance Association</i>	Peter L. Rousseau, <i>American Economic Association</i>
Philip Hoffman, <i>Economic History Association</i>	Gregor W. Smith, <i>Canadian Economics Association</i>
Arthur Kennickell, <i>American Statistical Association</i>	William Spriggs, <i>American Federation of Labor and Congress of Industrial Organizations</i>
Jack Kleinhenz, <i>National Association for Business Economics</i>	Bart van Ark, <i>The Conference Board</i>

Directors Emeriti

George Akerlof	Franklin Fisher	John J. Siegfried
Jagdish Bhagwati	Saul H. Hymans	Craig Swan
Don R. Conlan	Rudolph A. Oswald	
Ray C. Fair	Andrew Postlewaite	

Relation of the Directors to the Work and Publications of the National Bureau of Economic Research

1. The object of the NBER is to ascertain and present to the economics profession, and to the public more generally, important economic facts and their interpretation in a scientific manner without policy recommendations. The Board of Directors is charged with the responsibility of ensuring that the work of the NBER is carried on in strict conformity with this object.

2. The President shall establish an internal review process to ensure that book manuscripts proposed for publication DO NOT contain policy recommendations. This shall apply both to the proceedings of conferences and to manuscripts by a single author or by one or more co-authors but shall not apply to authors of comments at NBER conferences who are not NBER affiliates.

3. No book manuscript reporting research shall be published by the NBER until the President has sent to each member of the Board a notice that a manuscript is recommended for publication and that in the President's opinion it is suitable for publication in accordance with the above principles of the NBER. Such notification will include a table of contents and an abstract or summary of the manuscript's content, a list of contributors if applicable, and a response form for use by Directors who desire a copy of the manuscript for review. Each manuscript shall contain a summary drawing attention to the nature and treatment of the problem studied and the main conclusions reached.

4. No volume shall be published until forty-five days have elapsed from the above notification of intention to publish it. During this period a copy shall be sent to any Director requesting it, and if any Director objects to publication on the grounds that the manuscript contains policy recommendations, the objection will be presented to the author(s) or editor(s). In case of dispute, all members of the Board shall be notified, and the President shall appoint an ad hoc committee of the Board to decide the matter; thirty days additional shall be granted for this purpose.

5. The President shall present annually to the Board a report describing the internal manuscript review process, any objections made by Directors before publication or by anyone after publication, any disputes about such matters, and how they were handled.

6. Publications of the NBER issued for informational purposes concerning the work of the Bureau, or issued to inform the public of the activities at the Bureau, including but not limited to the NBER Digest and Reporter, shall be consistent with the object stated in paragraph 1. They shall contain a specific disclaimer noting that they have not passed through the review procedures required in this resolution. The Executive Committee of the Board is charged with the review of all such publications from time to time.

7. NBER working papers and manuscripts distributed on the Bureau's web site are not deemed to be publications for the purpose of this resolution, but they shall be consistent with the object stated in paragraph 1. Working papers shall contain a specific disclaimer noting that they have not passed through the review procedures required in this resolution. The NBER's web site shall contain a similar disclaimer. The President shall establish an internal review process to ensure that the working papers and the web site do not contain policy recommendations, and shall report annually to the Board on this process and any concerns raised in connection with it.

8. Unless otherwise determined by the Board or exempted by the terms of paragraphs 6 and 7, a copy of this resolution shall be printed in each NBER publication as described in paragraph 2 above.

Contents

	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	
	<i>Comment:</i> 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	
	<i>Comment:</i> Andrea Prat	
	4. The Impact of Artificial Intelligence on Innovation: An Exploratory Analysis	115
	Iain M. Cockburn, Rebecca Henderson, and Scott Stern	
	<i>Comment:</i> 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
	Betsy 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	
	<i>Comment:</i> 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

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

IV. MACHINE LEARNING AND ECONOMICS

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

Acknowledgments

This volume contains chapters and ideas discussed at the first NBER Conference on the Economics of Artificial Intelligence, held in September 2017 in Toronto. We thank all the authors and discussants for their contributions. Funds for the conference and book project were provided by the Sloan Foundation, the Canadian Institute for Advanced Research, and the Creative Destruction Lab at the University of Toronto. At the Sloan Foundation, Danny Goroff provided guidance that improved the overall agenda. The NBER digitization initiative, under the leadership of Shane Greenstein, was a key early supporter. We thank our dean, Tiff Macklem. In addition, Jim Poterba at the NBER has been generous, giving us the flexibility needed to bring this project together. Special thanks are due to Rob Shannon, Denis Healy, Carl Beck, and Dawn Bloomfield for managing the conference and logistics and to Helena Fitz-Patrick for guiding the book through the editorial process. Finally we thank our families, Gina, Natalie, Rachel, Amelia, Andreas, Belanna, Ariel, Annika, Anna, Sam, and Ben.

Artificial Intelligence, Automation, and Work

Daron Acemoglu and Pascual Restrepo

8.1 Introduction

The last two decades have witnessed major advances in artificial intelligence (AI) and robotics. Future progress is expected to be even more spectacular, and many commentators predict that these technologies will transform work around the world (Brynjolfsson and McAfee 2014; Ford 2016; Boston Consulting Group 2015; McKinsey Global Institute 2017). Recent surveys find high levels of anxiety about automation and other technological trends, underscoring the widespread concerns about their effects (Pew Research Center 2017).

These expectations and concerns notwithstanding, we are far from a satisfactory understanding of how automation in general, and AI and robotics in particular, impact the labor market and productivity. Even worse, much of the debate in both the popular press and academic circles centers around a false dichotomy. On the one side are the alarmist arguments that the oncoming advances in AI and robotics will spell the end of work by humans, while many economists on the other side claim that because technological breakthroughs in the past have eventually increased the demand for labor and wages, there is no reason to be concerned that this time will be any different.

In this chapter, we build on Acemoglu and Restrepo (2016), as well as

Daron Acemoglu is the Elizabeth and James Killian Professor of Economics at the Massachusetts Institute of Technology and a research associate of the National Bureau of Economic Research. Pascual Restrepo is assistant professor of economics at Boston University.

We are grateful to David Autor for useful comments. We gratefully acknowledge financial support from Toulouse Network on Information Technology, Google, Microsoft, IBM, and the Sloan Foundation. For acknowledgments, sources of research support, and disclosure of the authors' material financial relationships, if any, please see <http://www.nber.org/chapter/c14027.ack>.

Zeira (1998) and Acemoglu and Autor (2011) to develop a framework for thinking about automation and its impact on tasks, productivity, and work.

At the heart of our framework is the idea that automation and thus AI and robotics replace workers in tasks that they previously performed, and via this channel, create a powerful *displacement effect*. In contrast to presumptions in much of macroeconomics and labor economics, which maintain that productivity-enhancing technologies always increase overall labor demand, the displacement effect can reduce the demand for labor, wages, and employment. Moreover, the displacement effect implies that increases in output per worker arising from automation will not result in a proportional expansion of the demand for labor. The displacement effect causes a decoupling of wages and output per worker, and a decline in the share of labor in national income.

We then highlight several countervailing forces that push against the displacement effect and may imply that automation, AI, and robotics could increase labor demand. First, the substitution of cheap machines for human labor creates a *productivity effect*: as the cost of producing automated tasks declines, the economy will expand and increase the demand for labor in nonautomated tasks. The productivity effect could manifest itself as an increase in the demand for labor in the same sectors undergoing automation or as an increase in the demand for labor in nonautomating sectors. Second, *capital accumulation* triggered by increased automation (which raises the demand for capital) will also raise the demand for labor. Third, automation does not just operate at the extensive margin—replacing tasks previously performed by labor—but at the intensive margin as well, increasing the productivity of machines in tasks that were previously automated. This phenomenon, which we refer to as *deepening of automation*, creates a productivity effect but no displacement, and thus increases labor demand.

Though these countervailing effects are important, they are generally insufficient to engender a “balanced growth path,” meaning that even if these effects were powerful, ongoing automation would still reduce the share of labor in national income (and possibly employment). We argue that there is a more powerful countervailing force that increases the demand for labor as well as the share of labor in national income: the *creation of new tasks*, functions and activities in which labor has a comparative advantage relative to machines. The creation of new tasks generates a *reinstatement effect* directly counterbalancing the displacement effect.

Indeed, throughout history we have not just witnessed pervasive automation, but a continuous process of new tasks creating employment opportunities for labor. As tasks in textiles, metals, agriculture, and other industries were being automated in the nineteenth and twentieth centuries, a new range of tasks in factory work, engineering, repair, back-office, management, and finance generated demand for displaced workers. The creation of new tasks

is not an autonomous process advancing at a predetermined rate, but one whose speed and nature are shaped by the decisions of firms, workers, and other actors in society, and might be fueled by new automation technologies. First, this is because automation, by displacing workers, may create a greater pool of labor that could be employed in new tasks. Second, the currently most discussed automation technology, AI itself, can serve as a platform to create new tasks in many service industries.

Our framework also highlights that even with these countervailing forces, the adjustment of an economy to the rapid rollout of automation technologies could be slow and painful. There are some obvious reasons for this related to the general slow adjustment of the labor market to shocks, for example, because of the costly process of workers being reallocated to new sectors and tasks. Such reallocation will involve both a slow process of searching for the right matches between workers and jobs, and also the need for retraining, at least for some of the workers.

A more critical, and in this context more novel, factor is a potential *mismatch between technology and skills*—between the requirements of new technologies and tasks and the skills of the workforce. We show that such a mismatch slows down the adjustment of labor demand, contributes to inequality, and also reduces the productivity gains from both automation and the introduction of new tasks (because it makes the complementary skills necessary for the operation of new tasks and technologies more scarce).

Yet another major factor to be taken into account is the possibility of *excessive automation*. We highlight that a variety of factors (ranging from a bias in favor of capital in the tax code to labor market imperfections create a wedge between the wage and the opportunity cost of labor) and will push toward socially excessive automation, which not only generates a direct inefficiency, but also acts as a drag on productivity growth. Excessive automation could potentially explain why, despite the enthusiastic adoption of new robotics and AI technologies, productivity growth has been disappointing over the last several decades.

Our framework underscores as well that the singular focus of the research and the corporate community on automation, at the expense of other types of technologies including the creation of new tasks, could be another factor leading to a productivity slowdown because it forgoes potentially valuable productivity growth opportunities in other domains.

In the next section, we provide an overview of our approach without presenting a formal analysis. Section 8.3 introduces our formal framework, though to increase readability, our presentation is still fairly nontechnical (and formal details and derivations are relegated to the appendix). Section 8.4 contains our main results, highlighting both the displacement effect and the countervailing forces in our framework. Section 8.5 discusses the mismatch between skills and technologies, potential causes for slow pro-

ductivity growth and excessive automation, and other constraints on labor market adjustment to automation technologies. Section 8.6 concludes, and the appendix contains derivations and proofs omitted from the text.

8.2 Automation, Work, and Wages: An Overview

At the heart of our framework is the observation that robotics and current practice in AI are continuing what other automation technologies have done in the past: using machines and computers to substitute for human labor in a widening range of tasks and industrial processes.

Production in most industries requires the simultaneous completion of a range of tasks. For example, textile production requires production of fiber, production of yarn from fiber (e.g., by spinning), production of the relevant fabric from the yarn (e.g., by weaving or knitting), pretreatment (e.g., cleaning of the fabric, scouring, mercerizing and bleaching), dyeing and printing, finishing, as well as various auxiliary tasks including design, planning, marketing, transport, and retail.¹ Each one of these tasks can be performed by a combination of human labor and machines. At the dawn of the British Industrial Revolution, most of these tasks were heavily labor intensive. Many of the early innovations of that era were aimed at automating spinning and weaving by substituting mechanized processes for the labor of skilled artisans (Mantoux 1928).²

The mechanization of US agriculture offers another example of machines replacing workers in tasks they previously performed (Rasmussen 1982). In the first half of the nineteenth century, the cotton gin automated the labor-intensive process of separating the lint from the cotton seeds. In the second half of the nineteenth century, horse-powered reapers, harvesters, and plows replaced manual labor working with more rudimentary tools such as hoes, sickles, and scythes, and this process was continued with tractors in the twentieth century. Horse-powered threshing machines and fanning mills replaced workers employed in threshing and winnowing, two of the most labor-intensive tasks left in agriculture at the time. In the twentieth century, combine harvesters and a variety of other mechanical harvesters improved upon the horse-powered machinery, and allowed farmers to mechanically harvest several different crops.

Yet another example of automation comes from the development of the

1. See <http://textileguide.chemsec.org/find/get-familiar-with-your-textile-production-processes/>.

2. It was this displacement effect that motivated Luddites to smash textile machines and agricultural workers during the Captain Swing riots to destroy threshing machines. Though these workers often appear in history books as misguided, there was nothing misguided about their economic fears. They were quite right that they were going to be displaced. Of course, had they been successful, they might have prevented the Industrial Revolution from gaining momentum with potentially disastrous consequences for technological development and our subsequent prosperity.

factory system in manufacturing and its subsequent evolution. Beginning in the second half of the eighteenth century, the factory system introduced the use of machine tools such as lathes and milling machines, replacing the more labor-intensive production techniques relying on skilled artisans (Mokyr 1990). Steam power and later electricity greatly increased the opportunities for the substitution of capital for human labor. Another important turning point in the process of factory automation was the introduction of machines controlled via punch cards and then numerically controlled machines in the 1940s. Because numerically controlled machines were more precise, faster, and easier to operate than manual technologies, they enabled significant cost savings while also reducing the role of craft workers in manufacturing production. This process culminated in the widespread use of CNC (computer numerical control) machinery, which replaced the numerically controlled vintages (Groover 1983). A major new development was the introduction of industrial robots in the late 1980s, which automated many of the remaining labor-intensive tasks in manufacturing, including machining, welding, painting, palletizing, assembly, material handling, and quality control (Ayres and Miller 1983; Groover et al. 1986; Graetz and Michaels 2015; Acemoglu and Restrepo 2017).

Examples of automation are not confined to industry and agriculture. Computer software has already automated a number of tasks performed by white-collar workers in retail, wholesale, and business services. Software and AI-powered technologies can now retrieve information, coordinate logistics, handle inventories, prepare taxes, provide financial services, translate complex documents, write business reports, prepare legal briefs, and diagnose diseases. These technologies are set to become much better at these and other tasks during the next years (e.g., Brynjolfsson and McAfee 2014; Ford 2016).

As these examples illustrate, automation involves the substitution of machines for labor and leads to the displacement of workers from the tasks that are being automated. This displacement effect is not present—or present only incidentally—in most approaches to production functions and labor demand used in macroeconomics and labor economics. The canonical approach posits that production in the aggregate (or in a sector for that matter) can be represented by a function of the form $F(AL, BK)$, where L denotes labor and K is capital. Technology is assumed to take a “factor-augmenting” form, meaning that it multiplies these two factors of production as the parameters A and B do in this production function.

It might appear natural to model automation as an increase in B , that is, as capital-augmenting technological change. However, this type of technological change does not cause any displacement and always increases labor demand and wages (see Acemoglu and Restrepo 2016). Moreover, as our examples above illustrate, automation is not mainly about the development of more productive vintages of existing machines, but involves the intro-

duction of new machinery to perform tasks that were previously the domain of human labor.

Labor-augmenting technological change, corresponding to an increase in A , does create a type of displacement if the elasticity of substitution between capital and labor is small. But in general, this type of technological change also expands labor demand, especially if capital adjusts over the long run (see Acemoglu and Restrepo 2016). Moreover, our examples make it clear that automation does not directly augment labor; on the contrary, it transforms the production process in a way that allows more tasks to be performed by machines.

8.2.1 Tasks, Technologies, and Displacement

We propose, instead, a task-based approach, where the central unit of production is a task as in the textile example discussed above.³ Some tasks have to be produced by labor, while other tasks can be produced either by labor or by capital. Also, labor and capital have *comparative advantages* in different tasks, meaning that the relative productivity of labor varies across tasks. Our framework conceptualizes *automation* (or automation at the extensive margin) as an expansion in the set of tasks that can be produced with capital. If capital is sufficiently cheap or sufficiently productive at the margin, then automation will lead to the substitution of capital for labor in these tasks. This substitution results in a displacement of workers from the tasks that are being automated, creating the aforementioned displacement effect.

The displacement effect could cause a decline in the demand for labor and the equilibrium wage rate. The possibility that technological improvements that increase productivity can actually reduce the wage of *all* workers is an important point to emphasize because it is often downplayed or ignored.

With an elastic labor supply (or quasi-labor supply reflecting some labor market imperfections), a reduction in the demand for labor also leads to lower employment. In contrast to the standard approach based on factor-augmenting technological changes, a task-based approach immediately opens the way to productivity-enhancing technological developments that simultaneously reduce wages and employment.

8.2.2 Countervailing Effects

The presence of the displacement effect does not mean that automation will always reduce labor demand. In fact, throughout history, there are several periods where automation was accompanied by an expansion of

3. See Autor, Leavy, and Murnane (2003) and Acemoglu and Autor (2011). Different from these papers that develop a task-based approach focusing on inequality implications of technological change, we are concerned here with automation and the process of capital-replacing tasks previously performed by labor and their implications for wages and employment.

labor demand and even higher wages. There are a number of reasons why automation could increase labor demand.

1. *The Productivity Effect.* By reducing the cost of producing a subset of tasks, automation raises the demand for labor in nonautomated tasks (Autor 2015; Acemoglu and Restrepo 2016). In particular, automation leads to the substitution of capital for labor because at the margin, capital performs certain tasks more cheaply than labor used to. This reduces the prices of the goods and services whose production processes are being automated, making households effectively richer, and increasing the demand for all goods and services.

The productivity effect could manifest itself in two complementary ways. First, labor demand might expand in the same sectors that are undergoing automation.⁴ A telling example of this process comes from the effects of the introduction of automated teller machines (ATMs) on the employment of bank tellers. Bessen (2016) documents that concurrent with the rapid spread of ATMs—a clear example of automating technology that enabled these new machines to perform tasks that were previously performed more expensively by labor—there was an expansion in the employment of bank tellers. Bessen suggests that this is because ATMs reduced the costs of banking and encouraged banks to open more branches, raising the demand for bank tellers who then specialized in tasks that ATMs did not automate.

Another interesting example of this process is provided by the dynamics of labor demand in spinning and weaving during the British Industrial Revolution as recounted by Mantoux (1928). Automation in weaving (most notably, John Kay's fly shuttle) made this task cheaper and increased the price of yarn and the demand for the complementary task of spinning. Later automation in spinning reversed this trend and increased the demand for weavers. In the words of John Wyatt, one of the inventors of the spinning machine, installing spinning machines would cause clothiers to “then want more hands in every other branch of the trade, viz. weavers, shearmen, scourers, combers, etc.” (quoted in Mantoux 1928). This is also probably the reason why the introduction of Eli Whitney's cotton gin in 1793, which automated the labor-intensive process of separating the cotton lint from the seeds, appears to have led to greater demand for slave labor in southern plantations (Rasmussen 1982).

The productivity effect also leads to higher real incomes and thus to greater demand for all products, including those not experiencing automation. The greater demand for labor from other industries might then counteract the negative displacement effect of automation. The clearest historical example of this comes from the adjustment of the US and many European economies

4. This requires that the demand for the products of these sectors is elastic. Acemoglu and Restrepo (2017) refer to this channel as the price-productivity effect because it works by reducing the relative price of products that are being automated and restructuring production toward these sectors.

to the mechanization of agriculture. By reducing food prices, mechanization enriched consumers who then demanded more nonagricultural goods (Herrendorf, Rogerson, and Valentinyi 2013), and created employment opportunities for many of the workers dislocated by the mechanization process in the first place.⁵

This discussion also implies that, in contrast to the popular emphasis on the negative labor market consequences of “brilliant” and highly productive new technologies set to replace labor (e.g., Brynjolfsson and McAfee 2014; Ford 2016), the real danger for labor may come not from highly productive but from “so-so” automation technologies that are just productive enough to be adopted and cause displacement, but not sufficiently productive to bring about powerful productivity effects.

2. *Capital Accumulation.* As our framework in the next section clarifies, automation corresponds to an increase in the capital intensity of production. The high demand for capital triggers further accumulation of capital (e.g., by increasing the rental rate of capital). Capital accumulation then raises the demand for labor. This may have been an important channel of adjustment of the British economy during the Industrial Revolution and of the American economy in the first half of the twentieth century in the face of mechanization of agriculture, for in both cases there was rapid capital accumulation (Allen 2009; Olmstead and Rhode 2001).

As we discuss in the next section, under some (albeit restrictive) assumptions often adopted in neoclassical models of economic growth, capital accumulation can be sufficiently powerful that automation will always increase wages in the long run (see Acemoglu and Restrepo 2016), though the more robust prediction is that it will act as a countervailing effect.

3. *Deepening of Automation.* The displacement effect is created by automation at the extensive margin—meaning the expansion of the set of tasks that can be produced by capital. But what happens if technological improvements increase the productivity of capital in tasks that have already been automated? This will clearly not create additional displacement because labor was already replaced by capital in those tasks. But it will generate the same productivity effects we have already pointed out above. These productivity effects then raise labor demand. We refer to this facet of advances in automation technology as the deepening of automation (or as automation at the intensive margin because it is intensifying the productive use of machines).

A clear illustration of the role of deepening automation comes from the introduction of new vintages of machinery replacing older vintages used in already automated tasks. For instance, in US agriculture the replacement of

5. Acemoglu and Restrepo (2017) refer to it as a “scale effect” because in their setting it acted in a homothetic manner, scaling up demand from all sectors, though in general it could take a nonhomothetic form.

horse-powered reapers and harvesters by diesel tractors increased productivity, presumably with limited additional substitution of workers in agricultural tasks.⁶ In line with our account of the potential role of deepening automation, agricultural productivity and wages increased rapidly starting in the 1930s, a period that coincided with the replacement of horses by tractors (Olmstead and Rhode 2001; Manuelli and Seshadri 2014).

Another example comes from the vast improvements in the efficiency of numerically controlled machines used for metal cutting and processing (such as mills and lathes), as the early vintages controlled by punched cards were replaced by computerized models during the 1970s. The new computerized machines were used in the same tasks as the previous vintages, and so the additional displacement effects were probably minor. As a result, the transition to CNC (computer numerical control) machines increased the productivity of machinists, operators, and other workers in the industry (Groover 1983).

The three countervailing forces we have listed here are central for understanding why the implications of automation are much richer than the direct displacement effects might at first suggest, and why automation need not be an unadulterated negative force against the labor market fortunes of workers. Nevertheless, there is one aspect of the displacement effect that is unlikely to be undone by any of these four countervailing forces: as we show in the next section, automation necessarily makes the production process more capital intensive, reducing the share of labor in national income. Intuitively, this is because it entails the substitution of capital for tasks previously performed by labor, thus squeezing labor into a narrower set of tasks.

If, as we have suggested, automation has been ongoing for centuries, with or without powerful countervailing forces of the form listed here, we should have seen a “nonbalanced” growth process with the share of labor in national income declining steadily since the beginning of the Industrial Revolution. That clearly has not been the case (see, e.g., Kuznets 1966; Acemoglu 2009). This suggests that there have been other powerful forces making production more labor intensive and balancing the effects of automation. This is what we suggest in the next subsection.

8.2.3 New Tasks

As discussed in the introduction, periods of intensive automation have often coincided with the emergence of new jobs, activities, industries, and tasks. In nineteenth-century Britain, for example, there was a rapid expansion of new industries and jobs ranging from engineers, machinists, repairmen, conductors, back-office workers, and managers involved with

6. Nevertheless, the move from horse power to tractors contributed to a decline in agricultural employment via a different channel: tractors increased agricultural productivity, and because of inelastic demand, expenditure on agricultural products declined (Rasmussen 1982).

the introduction and operation of new technologies (e.g., Landes 1969; Chandler 1977; and Mokyr 1990). In early twentieth-century America, the mechanization of agriculture coincided with a large increase in employment in new industry and factory jobs (Kuznets 1966) among others in the burgeoning industries of farm equipment (Olmstead and Rhode 2001) and cotton milling (Rasmussen 1982). This is not just a historical phenomenon. As documented in Acemoglu and Restrepo (2016), from 1980 to 2010 the introduction and expansion of new tasks and job titles explains about half of US employment growth.

Our task-based framework highlights that the creation of new labor-intensive tasks (tasks in which labor has a comparative advantage relative to capital) may be the most powerful force balancing the growth process in the face of rapid automation. Without the demand for workers from new factory jobs, engineering, supervisory tasks, accounting, and managerial occupations in the second half of the nineteenth and much of the twentieth centuries, it would have been impossible to employ millions of workers exiting the agricultural sector and automated labor-intensive tasks.

In the same way that automation has a displacement effect, we can think of the creation of new tasks as engendering a *reinstatement effect*. In this way, the creation of new tasks has the opposite effect of automation. It always generates additional labor demand, which increases the share of labor in national income. Consequently, one powerful way in which technological progress could be associated with a balanced growth path is via the balancing of the impacts of automation by the creation of new tasks.

The creation of new tasks need not be an exogenous, autonomous process unrelated to automation, AI, and robotics for at least two reasons:

1. As emphasized in Acemoglu and Restrepo (2016), rapid automation may endogenously generate incentives for firms to introduce new labor-intensive tasks. Automation running ahead of the creation of new tasks reduces the labor share and possibly wages, making further automation less profitable and new tasks generating employment opportunities for labor more profitable for firms. Acemoglu and Restrepo (2016) show that this equilibrating force could be powerful enough to make the growth process balanced.

2. Some automation technology platforms, especially AI, may facilitate the creation of new tasks. A recent report by Accenture identified entirely new categories of jobs that are emerging in firms using AI as part of their production process (Accenture PLC 2017). These jobs include “trainers” (to train the AI systems), “explainers” (to communicate and explain the output of AI systems to customers), and “sustainers” (to monitor the performance of AI systems, including their adherence to prevailing ethical standards).

The applications of AI to education, health care, and design may also result in employment opportunities for new workers. Take education. Exist-

ing evidence suggests that many students, not least those with certain learning disabilities, will benefit from individualized education programs and personalized instruction (Kolb 1984). With current technology, it is prohibitively costly to provide such services to more than a small fraction of students. Applications of AI may enable the educational system to become more customized, and in the process create more jobs for education professionals to monitor, design, and implement individualized education programs. Similar prospects exist in health care and elderly care services.

8.2.4 Revisiting the False Dichotomy

The conceptual framework outlined above, which will be further elaborated in the next section, clarifies why the current debate is centered on a false dichotomy between disastrous and totally benign effects of automation.

Our task-based framework underscores that automation will always create a displacement effect. Unless neutralized by the countervailing forces, this displacement effect could reduce labor demand, wages, and employment. At the very least, this displacement effect implies that a falling share of output will accrue to labor. These possibilities push against the benign accounts emphasizing that technology always increases the demand for labor and benefits workers.

Our framework does not support the alarmist perspectives stressing the disastrous effects of automation for labor either. Rather, it highlights several countervailing forces that soften the impact of automation on labor. More important, as we have argued in the previous subsection, the creation of new labor-intensive tasks has been a critical part of the adjustment process in the face of rapid automation. The creation of new tasks is not just *manna* from heaven. There are good reasons why market incentives will endogenously lead to the creation of new tasks that gain strength when automation itself becomes more intensive. Also, some of the most defining automation technologies of our age, such as AI, may create a platform for the creation of new sets of tasks and jobs.

At the root of some of the alarmism is the belief that AI will have very different consequences for labor than previous waves of technological change. Our framework highlights that the past is also replete with automation technologies displacing workers, but this need not have disastrous effects for labor. Nor is it technologically likely that AI will replace labor in all or almost all of the tasks in which it currently specializes. This limited remit of AI can be best understood by contrasting the current nature and ambitions of AI with those of its first coming under the auspices of “cybernetics.” The intellectual luminaries of cybernetics, such as Norbert Wiener, envisaged the production of *Human-Level Artificial Intelligence*—computer systems capable of thinking in a way that could not be distinguished from human intelligence—replicating all human thought processes and faculties (Nilsson 2009). In 1965, Herbert Simon predicted that “machines will be capable,

within twenty years, of doing any work a man can do” (Simon 1965, 96). Marvin Minsky agreed, declaring in 1967 that “Within a generation, I am convinced, few compartments of intellect will remain outside the machine’s realm” (Minsky 1967, 2).

Current practice in the field of AI, especially in its most popular and promising forms based on deep learning and various other “big data” methods applied to unstructured data, eschews these initial ambitions and aims at developing *applied artificial intelligence*—commercial systems specializing in clearly delineated tasks related to prediction, decision-making, logistics, and pattern recognition (Nilsson 2009). Though many occupations involve such tasks—and so AI is likely to have a displacement effect in these tasks—there are still many human skills that we still cannot automate, including complex reasoning, judgment, analogy-based learning, abstract problem-solving, and a mixture of physical activity, empathy, and communication skills. This reading of the current practice of AI suggests that the potential for AI and related technological advances to automate a vast set of tasks is limited.

8.2.5 Flies in the Ointment

Our framework so far has emphasized two key ideas. First, automation does create a potential negative impact on labor through the displacement effect and also by reducing the share of labor in national income. But second, it can be counterbalanced by the creation of new tasks (as well as the productivity effect, capital accumulation and the deepening of automation, which tend to increase the demand for labor, even though they do not generally restore the share of labor in national income to its preautomation levels).

The picture we have painted underplays some of the challenges of adjustment, however. The economic adjustment following rapid automation can be more painful than the process we have outlined for a number of reasons.

Most straightforward, automation changes the nature of existing jobs, and the reallocation of workers from existing jobs and tasks to new ones is a complex and often slow process. It takes time for workers to find new jobs and tasks in which they can be productive, and periods during which workers are laid off from their existing jobs can create a depressed local or national labor market, further increasing the costs of adjustment. These effects are visible in recent studies that have focused on the adjustment of local US labor markets to negative demand shocks, such as Autor, Dorn, and Hanson (2013), who study the slow and highly incomplete adjustment of local labor markets in response to the surge in Chinese exports, Mian and Sufi (2014), who investigate the implications of the collapse in housing prices on consumption and local employment, and perhaps more closely related to our focus, Acemoglu and Restrepo (2017), who find employment and wage declines in areas most exposed to one specific type of automation, the introduction of industrial robots in manufacturing.

The historical record also underscores the painful nature of the adjustment. The rapid introduction of new technologies during the British Industrial Revolution ultimately led to rising labor demand and wages, but this was only after a protracted period of stagnant wages, expanding poverty, and harsh living conditions. During an eighty-year period extending from the beginning of the Industrial Revolution to the middle of the nineteenth century, wages stagnated and the labor share fell, even as technological advances and productivity growth were ongoing in the British economy, a phenomenon which Allen (2009) dubs the “Engel’s pause” (previously referred to as the “living standards paradox”; see Mokyr [1990]).

There should thus be no presumption that the adjustment to the changed labor market brought about by rapid automation will be a seamless, costless, and rapid process.

8.2.6 Mismatch between Skills and Technologies

It is perhaps telling that wages started growing in the nineteenth-century British economy only after mass schooling and other investments in human capital expanded the skills of the workforce. Similarly, the adjustment to the large supply of labor freed from agriculture in early twentieth-century America may have been greatly aided by the “high school movement,” which increased the human capital of the new generation of American workers (Goldin and Katz 2010). The forces at work here are likely to be more general than these examples. New tasks tend to require new skills. But to the extent that the workforce does not possess those skills, the adjustment process will be hampered. Even more ominously, if the educational system is not up to providing those skills (and if we are not even aware of the types of new skills that will be required so as to enable investments in them), the adjustment will be greatly impeded. Even the most optimistic observers ought to be concerned about the ability of the current US educational system to identify and provide such skills.

At stake here is not only the speed of adjustment, but potential productivity gains from new technologies. If certain skills are complementary to new technologies, their absence will imply that the productivity of these new technologies will be lower than otherwise. Thus the mismatch between skills and technologies not only slows down the adjustment of employment and wages, but holds back potential productivity gains. This is particularly true for the creation of new tasks. The fact that while there is heightened concerns about job losses from automation, many employers are unable to find workers with the right skills for their jobs underscores the importance of these considerations (Deloitte and the Manufacturing Institute 2011).

8.2.7 Missing Productivity and Excessive Automation

The issues raised in the previous subsection are important not least because a deep puzzle in any discussion of the impact of new technologies is miss-

ing productivity growth—the fact that while so many sophisticated technologies are being adopted, productivity growth has been slow. As pointed out by Gordon (2016), US productivity growth since 1974 (with the exception of the period from 1995 to 2004) compares dismally to its postwar performance. While the annual rate of labor productivity growth of the US economy averaged 2.7 percent between 1947 and 1973, it only averaged 1.5 percent between 1974 and 1994. Average productivity growth rebounded to 2.8 percent between 1995 and 2004, and then fell again to only 1.3 percent between 2005 and 2015 (Syverson 2017). How can we make sense of this?

One line of attack argues that there is plenty of productivity growth, but it is being mismeasured. But, as pointed out by Syverson (2017), the pervasive nature of this slow down, and the fact that it is even more severe in industries that have made greater investments in information technology (Acemoglu et al. 2014), make the productivity mismeasurement hypothesis unlikely to account for all of the slowdown.

Our conceptual framework suggests some possible explanations. They center around the possibility of “excessive automation,” meaning faster automation than socially desirable (Acemoglu and Restrepo 2016, 2018a). Excessive automation not only creates direct inefficiencies, but may also hold productivity growth down by wastefully using resources and displacing labor.

There are two broad reasons for excessive automation, both of which we believe to be important. The first is related to the biases in the US tax code, which subsidizes capital relative to labor. This subsidy takes the form of several different provisions, including additional taxes and costs employers have to pay for labor, subsidies in the form of tax credits and accelerated depreciation for capital outlays, and additional tax credit for interest rate deductions in case of debt-financed investments (AEI 2008; Tuzel and Zhang 2017). All of these distortions imply that at the margin, when a utilitarian social planner would be indifferent between capital and labor, the market would have an incentive to use machines, giving an inefficient boost to automation. This inefficiency could translate into slow productivity growth because the substitution of labor for machines worsens the misallocation of capital and labor.

Even absent such a fiscal bias, there are natural reasons for excessive automation. Labor market imperfections and frictions also tend to imply that the equilibrium wage is above the social opportunity cost of labor. Thus a social planner would use a lower shadow wage in deciding whether to automate a task than the market, creating another force toward excessive automation. The implications of this type of excessive automation would again include slower productivity growth than otherwise.

Finally, it is possible that automation has continued at its historical pace, or may have even accelerated recently, but the dismal productivity growth

performance we are witnessing is driven by a slowdown in the creation of new tasks or investment in other productivity-enhancing technologies (see Acemoglu and Restrepo 2016). A deceleration in the creation of new tasks and technologies other than automation would also explain why the period of slow productivity growth coincided with poor labor market outcomes, including stagnant median wages and a decline in the labor share.

There are natural reasons why too much emphasis on automation may come at the cost of investments in other technologies, including the creation of new tasks. For instance, in a setting where technologies are developed endogenously using a common set of resources (e.g., scientists), there is a natural trade-off between faster automation and investments in other types of technologies (Acemoglu and Restrepo 2016). Though it is at the moment impossible to know whether the redirection of research resources away from the creation of new tasks and toward automation has played an important role in the productivity slowdown, the almost singular focus in the corporate sector and research community on AI, applications of deep learning, and other big data methods to automate various tasks makes it at least plausible that there may be too much attention devoted to automation at the expense of other technological breakthroughs.

8.3 A Model of Automation, Tasks, and the Demand for Labor

In the previous section, we provided an intuitive discussion of how automation in general, and robotics and AI in particular, is expected to impact productivity and the demand for labor. In this section, we outline a formal framework that underlines these conclusions. Our presentation will be somewhat informal and without any derivations, which are all collected in the appendix.

8.3.1 A Task-Based Framework

We start with a simplified version of the task-based framework introduced in Acemoglu and Restrepo (2016). Aggregate output is produced by combining the services of a unit measure of tasks $x \in [N-1, N]$ according to the following Cobb-Douglas (unit elastic) aggregator

$$(1) \quad \ln Y = \int_{N-1}^N \ln y(x) dx,$$

where Y denotes aggregate output and $y(x)$ is the output of task x . The fact that tasks run between $N-1$ and N enables us to consider changes in the range of tasks, for example, because of the introduction of new tasks, without altering the total measure of tasks in the economy.

Each task can be produced by human labor, $\ell(x)$, or by machines, $m(x)$, depending on whether it has been (technologically) automated or not. In

particular, tasks $x \in [N - 1, I]$ are technologically automated, so can be produced by either labor or machines, while the rest are not technologically automated, so must be produced with labor:

$$(2) \quad y(x) = \begin{cases} \gamma_L(x)\ell(x) + \gamma_M(x)m(x) & \text{if } x \in [N - 1, I] \\ \gamma_L(x)\ell(x) & \text{if } x \in (I, N]. \end{cases}$$

Here, $\gamma_L(x)$ is the productivity of labor in task x and is assumed to be increasing, while $\gamma_M(x)$ is the productivity of machines in automated tasks. We assume that $\gamma_L(x)/\gamma_M(x)$ is increasing in x , and thus labor has a *comparative advantage* in higher-indexed tasks.⁷

The threshold I denotes the frontier of automation possibilities: it describes the range of tasks that can be automated using current available technologies in AI, industrial robots, various computer-assisted technologies, and other forms of “smart machines.”

We also simplify the discussion by assuming that both the supply of labor, L , and the supply of machines, K , are fixed and inelastic. The fact that the supply of labor is inelastic implies that changes in labor demand impact the share of labor in national income and the wage, but not the level of employment. We outline below how this framework can be easily generalized to accommodate changes in employment and unemployment.

8.3.2 Types of Technological Change

Our framework incorporates four different types of technological advances. All advances increase productivity, but as we will see with a very different impact on the demand for labor and wages.

1. *Labor-augmenting technological advances*: Standard approaches in macroeconomics and labor economics typically focus on labor-augmenting technological advances. Such technological changes correspond to increases (or perhaps an equi-proportionate increase) in the function $\gamma_L(x)$. Our analysis will show that they are in fact quite special, and the implications of automation and AI are generally very different from those of labor-augmenting advances.

2. *Automation (at the extensive margin)*: We consider automation to be an expansion of the set of tasks that are technologically automated as represented by the parameter I .

7. Our theoretical framework builds on Zeira (1998) who develops a model where firms produce intermediates using labor-intensive or capital-intensive technologies. Zeira focuses on how wages affect the adoption of capital-intensive production methods and how this margin amplifies productivity differences across countries and over time. In contrast, we focus on the implications of automation—modeled here as an increase in the set of tasks that can be produced by machines, represented by I —for the demand for labor, wages, and employment, and we also study the implications of the introduction of new tasks. In Acemoglu and Restrepo (2016), we generalize Zeira’s framework in a number of other dimensions and also endogenize the development of automation technologies and new tasks.

3. *Deepening of automation (or automation at the intensive margin)*: Another dimension of advances in AI and robotics technology will tend to increase the productivity of machines in tasks that are already automated, for example, by replacing existing machines with newer, more productive vintages. In terms of our model, this corresponds to an increase in the $\gamma_M(x)$ function for tasks $x < I$. We will see that this type of deepening of automation has very different implications for labor demand than automation (at the extensive margin).

4. *Creation of new tasks*: As emphasized in Acemoglu and Restrepo (2016), another important aspect of technological change is the creation of new tasks and activities in which labor has a comparative advantage. In our model this can be captured in the simplest possible way by an increase in N .

8.3.3 Equilibrium

Throughout, we denote the equilibrium wage rate by W and the equilibrium cost of machines (or the rental rate) by R . An equilibrium requires firms to choose the cost-minimizing way of producing each task and labor and capital markets to clear.

To simplify the discussion, we impose the following assumption

$$(A1) \quad \frac{\gamma_L(N)}{\gamma_M(N-1)} > \frac{W}{R} > \frac{\gamma_L(I)}{\gamma_M(I)}.$$

The second inequality implies that all tasks in $[N-1, I]$ will be produced by machines. The first inequality implies that the introduction of new tasks—an increase in N —will increase aggregate output. This assumption is imposed on the wage-to-rental rate ratio, which is an endogenous object; the appendix provides a condition on the stock of capital and labor that is equivalent to this assumption (see assumption [A2]).

We also show in the appendix that aggregate output (GDP) in the equilibrium takes the form

$$(3) \quad Y = B \left(\frac{K}{I - N + 1} \right)^{I - N + 1} \left(\frac{L}{N - I} \right)^{N - I},$$

where

$$(4) \quad B = \exp \left(\int_{N-1}^I \ln \gamma_M(x) dx + \int_I^N \ln \gamma_L(x) dx \right).$$

Aggregate output is given by a Cobb-Douglas aggregate of the capital stock and employment. This resulting aggregate production function in equation (3) is itself derived from the allocation of the two factors of production to tasks. More important, the exponents of capital and labor in this production function depend on the extent of automation, I , and the creation of new tasks, as captured by N .

Central to our focus is not only the impact of new technologies on pro-

ductivity, but also on the demand for labor. The appendix shows that the demand for labor can be expressed as

$$(5) \quad W = (N - I) \frac{Y}{L}.$$

This equation is intuitive in view of the Cobb-Douglas production function in equation(3), since it shows that the wage (the marginal product of labor) is equal to the average product of labor—which we will also refer to as “productivity”—times the exponent of labor in the aggregate production function.

Equation (5) implies that the share of labor in national income is given by

$$(6) \quad s_L = \frac{WL}{Y} = N - I.$$

8.4 Technology and Labor Demand

8.4.1 The Displacement Effect

Our first result shows that automation (at the extensive margin) indeed creates a *displacement effect*, reducing labor demand as emphasized in section 8.2, but also that it is counteracted by a *productivity effect*, pushing toward greater labor demand.

Specifically, from equation (5) we directly obtain

$$(7) \quad \frac{d \ln W}{dI} = \underbrace{\frac{d \ln(N - I)}{dI}}_{\text{Displacement effect} < 0} + \underbrace{\frac{d \ln(Y / L)}{dI}}_{\text{Productivity effect} > 0}.$$

Without the productivity effect, automation would always reduce labor demand because it is directly replacing labor in tasks that were previously performed by workers. Indeed, if the productivity effect is limited, automation will reduce labor demand and wages.

8.4.2 Counteracting the Displacement Effect I: The Productivity Effects

The productivity effect, on the other hand, captures the important idea that by increasing productivity, automation raises labor demand in the tasks that are not automated. As highlighted in the previous section, there are two complementary manifestations of the productivity effect. The first works by increasing the demand for labor in nonautomated tasks in the industries where automation is ongoing. The second works by raising the demand for labor in other industries. The productivity effect shown in equation (7) combines these two mechanisms.

One important implication of the decomposition in equation (7) is that, in

contrast to some popular discussions, the new AI and robotics technologies that are more likely to reduce the demand for labor are not those that are brilliant and highly productive, but those that are “so-so”—just productive enough to be adopted but not much more productive or cost-saving than the production processes that they are replacing. Interestingly, and related to our discussion on missing productivity, if new automation technologies are so-so, they would not bring major improvements in productivity either.

To elaborate further on this point and to understand the productivity implications of automation technologies better, let us also express the productivity effect in terms of the physical productivities of labor and machines and factor prices as follows:

$$\frac{d\ln(Y/L)}{dI} = \ln\left(\frac{W}{\gamma_L(I)}\right) - \ln\left(\frac{R}{\gamma_M(I)}\right) > 0.$$

The fact that this expression is positive, and that new automation technologies will be adopted, follows from assumption (A1). Using this expression, the overall impact on labor demand can be alternatively written as

$$(8) \quad \frac{d\ln W}{dI} = - \underbrace{\frac{1}{N-I}}_{\text{Displacement effect} < 0} + \underbrace{\ln\left(\frac{W}{\gamma_L(I)}\right) - \ln\left(\frac{R}{\gamma_M(I)}\right)}_{\text{Productivity effect} > 0}.$$

This expression clarifies that the displacement effect of automation will dominate the productivity effect and thus reduce labor demand (and wages) when $\gamma_M(I)/R \approx \gamma_L(I)/W$, which is exactly the case when new technologies are so-so—only marginally better than labor at newly automated tasks. In contrast, when $\gamma_M(I)/R \gg \gamma_L(I)/W$, automation will increase productivity sufficiently to raise the demand for labor and wages.

Turning next to the implications of automation for the labor share, equation (6) implies

$$(9) \quad \frac{ds_L}{dI} = -1 < 0,$$

so that regardless of the magnitude of the productivity effect, automation always reduces the share of labor in national income. This negative impact on the labor share is a direct consequence of the fact that automation always increases productivity more than the wage, $d\ln(Y/L)/dI > d\ln W/dI$ (itself directly following from equation [7], which shows that the impact on wages is given by the impact on productivity minus the displacement effect).

The implications of standard labor-augmenting technological change, which corresponds to a (marginal) shift-up of the $\gamma_L(x)$ schedule, are very different from those of automation. Labor-augmenting technologies leave the form of the wage equation (5) unchanged, and increase average output

per worker, Y/L , and the equilibrium wage, W , proportionately, and thus do not impact the share of labor in national income.⁸

8.4.3 Counteracting the Displacement Effect II: Capital Accumulation

We have so far emphasized the displacement effect created by new automation technologies. We have also seen that the productivity effect counteracts the displacement effects to some degree. In this and the next subsection, we discuss two additional countervailing forces.

The first force is capital accumulation. The analysis so far assumed that the economy has a fixed supply of capital that could be devoted to new machines (automation technologies). As a result, a further increase in automation (at the extensive margin) increases the demand for capital and thus the equilibrium rental rate, R . This may be understood as the short-run effect of automation.

Instead, we may envisage the “medium-run” effect as the impact of these technologies after the supply of machines used in newly automated tasks expands as well. Because machines and labor are q -complements, an increase in the capital stock, with the level of employment held constant at L , increases the real wage and reduces the rental rate. Equation (8) shows that this change in factor prices makes the productivity effect more powerful and the impact on the wage more likely to be positive.

In the limit, if capital accumulation fixes the rental rate at a constant level (which will be the case, for example, when we have a representative household with exponential discounting and time-separable preferences), the productivity effect will always dominate the displacement effect.⁹

Crucially, however, equation (6) still applies, and thus automation continues to reduce the labor share, even after the adjustment of the capital stock.

8.4.4 Counteracting the Displacement Effect III: Deepening of Automation

Another potentially powerful force counteracting the displacement effect from automation at the extensive margin comes from the deepening of automation (or automation at the intensive margin), for example, because of improvements in the performance of already-existing automation technolo-

8. A small shift-up of $\gamma_L(x)$ does not violate assumption (A1) because at the margin it was strictly cost-saving to use machines. A larger labor-augmenting technological change may result in a violation of assumption (A1). At this point, only tasks below an endogenous threshold $\tilde{I} < I$ would be automated, and labor-augmenting technologies could also reduce \tilde{I} , increasing the labor share in national income.

9. Assuming that production exhibits constant returns to scale, the productivity gains from any technology accrue to both capital and labor. In particular, for any constant returns to scale production function, we have $d \ln Y|_{K,L} = s_L d \ln W + (1 - s_L) d \ln R$, where $d \ln Y|_{K,L} > 0$ denotes the productivity gains brought by technology holding the use of capital and labor constant, and s_L is the labor share. If the rental rate is constant in the long run, then $d \ln R = 0$ and all productivity gains accrue to the relatively inelastic factor, labor.

gies or the replacement of such technologies with newer, more productive vintages. This increase in the productivity of machines in tasks that are already automated corresponds in our model to an increase in the function $\gamma_M(x)$ in tasks below I .

To explore the implications of this type of change in the simplest possible way, let us suppose that $\gamma_M(x) = \gamma_M$ in all automated tasks, and consider an increase in the productivity of machines by $d\ln\gamma_M > 0$, with no change in the extensive margin of automation, I . The implications of this change in the productivity of machines on equilibrium wages and productivity can be obtained as

$$d\ln W = d\ln Y / L = (I - N + 1)d\ln\gamma_M > 0.$$

Hence, deepening of automation will tend to increase labor demand and wages, further counteracting the displacement effect. Note, however, that as with capital accumulation, in our model this has no impact on the share of labor in national income, as can be seen from the fact that wages and productivity increase by exactly the same amount.

8.4.5 New Tasks and the Comparative Advantage of Labor

Much more powerful than the countervailing effects of capital accumulation and the deepening of automation is the creation of new tasks in which labor has a comparative advantage. These tasks include both new, more complex versions of existing tasks and the creation of new activities, which are made possible by advances in technology. In terms of our framework, they correspond to increases in N .

An increase in N —the creation of new tasks—raises productivity by

$$\frac{d\ln Y / L}{dN} = \ln\left(\frac{R}{\gamma_M(N-1)}\right) - \ln\left(\frac{W}{\gamma_L(N)}\right) > 0,$$

which is positive from assumption (A1).

More important for our focus here, the creation of new tasks also increases labor demand and equilibrium wages by creating a *reinstatement effect* counteracting the displacement effect. In particular,

$$(10) \quad \frac{d\ln W}{dN} = \underbrace{\ln\left(\frac{R}{\gamma_M(n-1)}\right) - \ln\left(\frac{W}{\gamma_L(N)}\right)}_{\text{Productivity effect} > 0} + \underbrace{\frac{1}{N-I}}_{\text{Reinstatement effect} > 0}.$$

In contrast to capital accumulation and the deepening of automation, which increase the demand for labor but do not affect the labor share, equation (6) implies that new tasks increase the labor share, that is,

$$\frac{ds_L}{dN} = 1.$$

The centrality of new tasks can be understood when viewed from a complementary historical angle. Automation is not a recent phenomenon. As we already discussed in section 8.2, the history of technology of the last two centuries is full of examples of automation, ranging from weaving and spinning machines to the mechanization of agriculture, as discussed in the previous section. Even with capital accumulation and the deepening of automation, if there were no other counteracting force, we would see the share of labor in national income declining steadily. Our conceptual framework highlights a major force preventing such a decline—the creation of new tasks in which labor has a comparative advantage.

This can be seen by putting together equations (7) and (10), which yields

$$(11) \quad d \ln W = \left[\ln \left(\frac{R}{\gamma_M(N-1)} \right) - \ln \left(\frac{W}{\gamma_L(N)} \right) \right] dN \\ + \left[\ln \left(\frac{W}{\gamma_L(I)} \right) - \ln \left(\frac{R}{\gamma_M(I)} \right) \right] dI + \frac{1}{N-I} (dN - dI),$$

and also from equation (6),

$$ds_L = dN - dI.$$

For the labor share to remain stable and for wages to increase in tandem with productivity, as has been the case historically, we need I —capturing the extensive margin of automation—to grow by the same amount as the range of new tasks, N . When that happens, equilibrium wages grow proportionately with productivity, and the labor share, s_L , remains constant, as can be seen from the fact that the first line of equation (11) is in this case equal to the increase in productivity or gross domestic product (GDP) per worker. Indeed, rewriting equation (11) imposing $dN = dI$, we have

$$d \ln W = \left[\ln \left(\frac{\gamma_L(N)}{\gamma_M(N-1)} \right) - \ln \left(\frac{\gamma_L(I)}{\gamma_M(I)} \right) \right] dI > 0,$$

which is strictly positive because of assumption (A1).

8.4.6 A False Dichotomy: Recap

With our conceptual framework explicated in a more systematic manner, we can now briefly revisit the false dichotomy highlighted in the introduction. Our analysis (in particular equation [7]) highlights that there is always a negative displacement effect on labor resulting from automation. Equation (11) reiterates that there is no presumption that this displacement effect could not reduce overall demand for labor.

However, several countervailing effects imply that a negative impact from automation on labor demand is not a forgone conclusion. Most important, the productivity effect could outweigh the displacement effect, leading to an expansion in labor demand and equilibrium wages from automation. The

presence of the productivity effect as counterweight to the displacement created by automation highlights an important conceptual issue, however. In contrast to the emphasis in the popular discussions it is not the brilliant, superproductive automation technologies that threaten labor, but the “so-so” ones that create the displacement effect as they replace labor in tasks that it previously performed, but do not engender the countervailing productivity effect.

The productivity effect is supplemented by the capital accumulation that automation sets in motion and the deepening of automation, which increases the productivity of machines in tasks that have already been automated. But even with these countervailing effects, equation (9) shows that automation will always reduce the share of labor in national income. All the same, this does not signal the demise of labor either, because the creation of new tasks in which labor has a comparative advantage could counterbalance automation, which is our interpretation of why the demand for labor has kept up with productivity growth in the past despite several rapid waves of automation.

Our framework suggests that the biggest shortcoming of the alarmist and the optimist views is their failure to recognize that the future of labor depends on the balance between automation and the creation of new tasks. Automation will often lead to a healthy growth of labor demand and wages if it is accompanied with a commensurate increase in the set of tasks in which labor has a comparative advantage—a feature that alarmists seem to ignore. Even though there are good economic reasons for why the economy will create new tasks, this is neither a forgone conclusion nor something we can always count on—as the optimists seem to assume. Artificial intelligence and robotics could be permanently altering this balance, causing automation to pace ahead of the creation of new tasks with negative consequences for labor, at the very least in regard to the share of labor in national income.

8.4.7 Generalizations

Many of the features adopted in the previous subsection are expositional simplifications. In particular, the aggregate production function (1) can be taken to be any constant elasticity of substitution aggregate. One implication of this would be that aggregate output in equation (3) would be a constant elasticity aggregate itself. This does not affect any of our main conclusions, including the negative impact of automation on the labor share (see Acemoglu and Restrepo 2016).¹⁰

We also do not need assumption (A1) for any of the results. If the second

10. Recent work by Aghion, Jones, and Jones (2017) points out, however, that if the elasticity of substitution between tasks is less than one and there is an exogenous and high saving rate, the labor share might asymptote to a positive value even with continuously ongoing automation.

inequality in this assumption does not hold, changes in automation technology have no impact on the equilibrium because it is not cost effective to adopt all available automation technologies (for this reason, in the general case, Acemoglu and Restrepo [2016] distinguish technologically automated tasks from equilibrium automation). Given our focus here, there is no loss of generality in making this assumption.

A final feature that is worth commenting on is the fact that in the aggregate production function (1), the limits of integration are $N - 1$ and N , ensuring that the total measure of tasks is one. This is useful for several reasons. First, when the introduction of new tasks expands the total measure of tasks, it becomes more challenging to obtain a balanced growth path (see Acemoglu and Restrepo 2016). Second, in this case some minor modifications are necessary so that an expansion in the total measure of tasks leads to productivity improvements. In particular, consider the general case where the elasticity of substitution between tasks is not necessarily equal to one. If it is greater than one, an increase in N leads to higher productivity, but not necessarily when it is less than or equal to one. In this latter case, we then need to introduce direct productivity gains from task variety. For example, in the present case where the elasticity of substitution between tasks is equal to one, we could modify (1) to $\ln Y = (1/N) \sum_0^N \ln[N^{1+\alpha}y(i)]$, where $\alpha \geq 0$ represents these productivity gains from task variety and ensures that the qualitative results explicit here continue to apply.

8.4.8 Employment and Unemployment

An additional generalization concerns the endogenous adjustment of employment in the face of new automation technologies. We have so far taken labor to be supplied inelastically for simplicity. There are two ways in which the level of employment responds to the arrival of new technologies. The first is via a standard labor supply margin. Acemoglu and Restrepo (2016) show that the endogenous adjustment of labor supply, including income effects and the substitution of consumption and leisure, links the level of employment to the share of labor in national income.

The second possibility is through labor market frictions, for example, as in Acemoglu and Restrepo (2018a). Under appropriate assumptions, the endogenous level of employment in this case is also a function of the share of labor in national income. Though both models with and without labor market frictions endogenize employment as a function of the labor share, their normative implications are potentially different, as we discuss below.

For now, however, the more important implication of such extensions is to link the level of employment (or unemployment) to labor demand. Automation, when it reduces labor demand, will also reduce the level of employment (or increase the level of unemployment). Moreover, because the supply of labor depends on the labor share, in our framework automation results in a reduction in employment (or an increase in unemployment). As such, our analysis so far also sheds light on (and clarifies the conditions for)

the claims that new automation technologies will reduce employment. It also highlights, however, that the fact that automation has been ongoing does not condemn the economy to a declining path of employment. If automation is met by equivalent changes in the creation of new tasks, the share of labor in national income can remain stable and ensure a stable level of employment (or unemployment) in the economy.

8.5 Constraints and Inefficiencies

Even in the presence of the countervailing forces limiting the displacement effect from automation, there are potential inefficiencies and constraints limiting the smooth adjustment of the labor market and hindering the productivity gains from new technologies.

Here we focus on how the mismatch between skills and technologies not only increases inequality, but also hinders the productivity gains from automation and new tasks. We then explore the possibility that, concurrent with rapid automation, we are experiencing a slowdown in the creation of new tasks, which could result in slow productivity growth. Finally, we examine how a range of factors leads to excessive automation, which not only creates inefficiency but also hinders productivity.

8.5.1 Mismatch of Technologies and Skills

The emphasis on the creation of new tasks counterbalancing the potential negative effects of automation on the labor share and the demand for labor ignores an important caveat and constraint: the potential mismatch between the requirements of new technologies (tasks) and the skills of the workforce. To the extent that new tasks require skilled employees or even new skills to be acquired, the adjustment may be much slower than our analysis so far suggests.

To illustrate these ideas in the simplest possible fashion, we follow Acemoglu and Restrepo (2016) and assume that there are two types of workers, low-skill with supply L and high-skill with supply H , both of them supplied inelastically. We also assume that low-skill workers can only perform tasks below a threshold $S \in (I, N)$, while high-skill workers can perform all tasks. For simplicity, we assume that the productivity of both low-skill and high-skill workers in the tasks that they can perform is still given by $\gamma_L(x)$.¹¹ Low-skill workers earn a wage W_L and high-skill workers earn a wage W_H .

11. We can also introduce differential comparative advantages and also an absolute productivity advantage for high-skill workers, though we choose not to do so to increase transparency (see Acemoglu and Restrepo 2016). The more restrictive assumption here is that automation happens at the bottom of the range of tasks. In general, automation could take place in the middle range, and its impact would depend on whether automated tasks are competing predominantly against low-skill or high-skill workers (see Acemoglu and Autor 2011; Acemoglu and Restrepo 2018b).

In this simple extension of the framework presented so far, the threshold S can be considered as an inverse measure of the mismatch between new technologies and skills. A greater value of S implies that there are plenty of additional tasks for low-skill workers, while a low value of S implies the presence of only a few tasks left that low-skill workers can perform.

Assuming that in equilibrium $W_H > W_L$,¹² which implies that low-skill workers will perform all tasks in the range (I, S) , equilibrium wages satisfy

$$W_H = \frac{Y}{H}(N - S) \text{ and } W_L = \frac{Y}{L}(S - I).$$

Thus, the impact of automation on inequality—defined here as the wage premium between high- and low-skill workers—is given by

$$\frac{d \ln W_H / W_L}{dI} = \frac{1}{S - I} > 0.$$

This equation shows that automation increases inequality. This is not surprising, since the tasks that are automated are precisely those performed by low-skill workers. But in addition, it also demonstrates that the impact of automation on inequality becomes worse when there is a severe skill mismatch—the threshold S is close to I . In this case, displaced workers will be squeezed into a very small range of tasks, and hence, each of these tasks will receive a large number of workers and will experience a substantial drop in price, which translates into a sharp decline in the wage of low-skill workers. In contrast, when S is large, displaced workers can spread across a larger set of tasks without depressing their wage as much.

A severe mismatch also affects the productivity gains from automation. In particular, we have

$$\frac{d \ln(Y/L)}{dI} = \ln\left(\frac{W_L}{\gamma_L(I)}\right) - \ln\left(\frac{R}{\gamma_M(I)}\right) > 0.$$

This equation shows that the productivity gains from automation depend positively on W_L/R : it is precisely when displaced workers have a high opportunity cost that automation raises productivity. Using the fact that $R = (Y/K)(I - N + 1)$, we obtain

$$\frac{W_L}{R} = \frac{S - I}{I - N + 1} \frac{K}{L}.$$

A worse mismatch (a lower S) reduces the opportunity cost of displaced workers further, and via this channel, it makes automation less profitable. This is because a severe mismatch impedes reallocation, reducing the productivity gains of freeing workers from automated tasks.

12. This is equivalent to $[(N - S)/(S - I)] > (H/L)$, so that high-skill workers are scarce relative to the range of tasks that only they can produce.

Equally important are the implications of a skill mismatch for the productivity gains from new tasks. Namely,

$$\frac{d\ln(Y/L)}{dN} = \ln\left(\frac{R}{\gamma_M(N-I)}\right) - \ln\left(\frac{W_H}{\gamma_H(N)}\right) > 0,$$

which depends negatively on W_H/R : it is precisely when high-skill workers have a relatively high wage that the gains from new tasks will be limited. With similar arguments to before, we also have

$$\frac{W_H}{R} = \frac{N-S}{I-N+1} \frac{K}{L},$$

which implies that in the presence of a worse mismatch (a lower S), the productivity gains from new tasks will be limited. This is because new tasks require high-skill workers who are scarce and expensive when S is low.

An important implication of this analysis is that to limit increasing inequality and to best deploy new tasks and harness the benefits of automation, society may need to simultaneously increase the supply of skills. A balanced growth process requires not only automation and the creation of new tasks to go hand-in-hand, but also the supply of high-skill workers to grow in tandem with these technological trends.

8.5.2 Automation at the Expense of New Tasks

As discussed in section 8.2, a puzzling aspect of recent macroeconomic developments has been the lack of robust productivity growth despite the bewildering array of new technologies. Our conceptual framework provides three novel (and at least to us, more compelling) reasons for slow productivity growth. The first was the skill mismatch discussed in the previous subsection.

The second one, discussed in this subsection, is that concurrent with the rapid introduction of new automation technologies, we may be experiencing a slowdown in the creation of new tasks and investments in other technologies that benefit labor.

This explanation comes in two flavors. First, we may be running out of good ideas to create new jobs, sectors, and products capable of expanding the demand for labor (e.g., Gordon 2016; Bloom et al. 2017), even if automation continues at a healthy or accelerating pace. Alternatively, the rapid introduction of new automation technologies may redirect resources that were devoted to other technological advances, in particular, the creation of new tasks (see Acemoglu and Restrepo 2016). To the extent that the recent enthusiasm—or even “frenzy”—about deep learning and some aspects of AI can be viewed as such a redirection, our framework pinpoints a potential powerful mechanism for slower productivity growth in the face of rapid automation.

Both explanations hinge on the redirection of research activity from the

creation of new tasks to automation—in the first case exogenously and in the second for endogenous reasons. Recall from our analysis so far that the productivity gains from new tasks in our baseline framework are given by

$$\frac{d\ln(Y/L)}{dN} = \ln\left(\frac{R}{\gamma_M(N-1)}\right) - \ln\left(\frac{W}{\gamma_L(N)}\right) > 0,$$

while productivity gains from automation are

$$\frac{d\ln(Y/L)}{dI} = \ln\left(\frac{W}{\gamma_L(I)}\right) - \ln\left(\frac{R}{\gamma_M(I)}\right) > 0.$$

If the former expression is greater than the latter, then the redirection of research effort from the creation of new tasks toward automation, or a lower research efficiency in creating new tasks, will lead to a slowdown of productivity growth, even if advances in automation are accelerating and being adopted enthusiastically. This conclusion is strengthened if additional effort devoted to automation at the expense of the creation of new tasks runs into diminishing returns.

8.5.3 Excessive Automation

In this subsection, we highlight the third reason for why there may be modest productivity growth: socially excessive automation (see Acemoglu and Restrepo 2016, 2018a).

To illustrate why our framework can generate excessive automation, we modify the assumption that the supply of capital, K , is given, and instead suppose that machines used in automation are produced—as intermediate goods—using the final good at a fixed cost R . Moreover, suppose that because of subsidies to capital, accelerated depreciation allowances, tax credit for debt-financed investment or simply because of the tax cost of employing workers, capital receives a marginal subsidy of $\tau > 0$.

Given this subsidy, the rental rate for machines is $R(1 - \tau)$, and assumption (A1) now becomes

$$\frac{\gamma_L(N)}{\gamma_M(N-1)} > \frac{W}{R(1-\tau)} > \frac{\gamma_L(I)}{\gamma_M(I)}.$$

Let us now compute GDP as value added, subtracting the cost of producing machines. This gives us

$$\text{GDP} = Y - RK.$$

Suppose next that there is an increase in automation. Then we have

$$\frac{d\text{GDP}}{dI} = \frac{dY}{dI}\Big|_K + R(1-\tau)\frac{dK}{dI} - R\frac{dK}{dI},$$

which simplifies to

$$\frac{dGDP}{dI} = \underbrace{\ln\left(\frac{W}{\gamma_L(I)}\right) - \ln\left(\frac{R(1-\tau)}{\gamma_M(I)}\right)}_{\text{Productivity effect} > 0} - \underbrace{R\tau \frac{dK}{dI}}_{\text{Excessive automation} < 0}.$$

The first term is positive and captures the productivity increase generated by automation. However, when $\tau > 0$ —so that the real cost of using capital is distorted—we have an additional negative effect originating from excessive automation.¹³ At the root of this negative effect is the fact that subsidies induce firms to substitute capital for labor even when this is not socially cost-saving (though it is privately beneficial because of the subsidy).

This conclusion is further strengthened when there are also labor market frictions as pointed out in section 8.2. To illustrate this point in the simplest possible fashion, let us assume that there is a threshold $J \in (I, N)$ such that, when performing the tasks in $[I, J]$, workers earn rents $\omega > 0$ proportional to their wage in other tasks. In particular, workers are paid a wage W to produce tasks in $[J, N]$, and a wage $W(1 + \omega)$ to produce tasks in (I, J) .¹⁴ Let L_A denote the total amount of labor allocated to the tasks in (I, J) , and note that these are the workers that will be displaced by automation, that is, by a small increase in I . Given this additional distortion, assumption (A1) now becomes

$$\frac{\gamma_L(N)}{\gamma_M(N-1)} > \frac{W}{R(1-\tau)} > \frac{1}{1+\omega} \frac{\gamma_L(I)}{\gamma_M(I)}.$$

The demand for labor in tasks where workers earn rents is now

$$L_A = \frac{Y}{W(1+\omega)}(J-I).$$

The demand for labor in tasks where workers do not earn rents is

$$L - L_A = \frac{Y}{W}(N - J).$$

Dividing these two expressions, we obtain the equilibrium condition for L_A ,

$$\frac{L_A}{L - L_A} = \frac{1}{1+\omega} \frac{J-I}{N-J},$$

13. We show in the appendix that $K = (Y/R)(I - N + 1)$, which implies that K increases in I .

14. The assumption that there are rents only in a subset of tasks is adopted for simplicity. The same results apply (a) when there are two sectors and one of the sectors has higher rents/wages for workers and enables automation and (b) there is an endogenous margin between employment and nonemployment and labor market imperfections (such as search, bargaining, or efficiency wages) that create a wedge between wages and outside options. In both cases the automation decisions of firms fail to internalize the gap between the market wage and the opportunity cost of labor, leading to excessive automation (see Acemoglu and Restrepo 2018a).

which implies that the total number of workers earning rents declines with automation.

Moreover, the appendix shows that (gross) output is now given by

$$(12) \quad Y = B \left(\frac{K}{I - N + 1} \right)^{I - N + 1} \left(\frac{L_A}{J - I} \right)^{J - I} \left(\frac{L - L_A}{N - J} \right)^{N - J},$$

and GDP is still given by $Y - RK$. Equation (12) highlights that there is now a misallocation of labor across tasks—output can be increased by allocating more workers to tasks (I, J) where their marginal product is greater (because of the rents they are earning).

Equation (12) further implies that the impact of automation on GDP is given by

$$\frac{dGDP}{dI} = \underbrace{\ln \left(\frac{W(1 + \omega)}{\gamma_L(I)} \right) - \ln \left(\frac{R(1 - \tau)}{\gamma_M(I)} \right)}_{\text{Productivity effect} > 0} - \underbrace{R\tau \frac{dK}{dI}}_{\text{Excessive automation} < 0} + \underbrace{W\omega \frac{dL_A}{dI}}_{\text{Excessive displacement of labor} < 0}.$$

The new term $W\omega(dL_A/dI)$ captures the first-order losses from a decline in employment in tasks (I, J) . These losses arise because by automating jobs where workers earn rents, firms are effectively displacing workers to other tasks in which they have a lower marginal product and earn a strictly lower wage, which increases the extent of misallocation.

The point highlighted here is much more general. Without labor market frictions, automation increases GDP (and net output), so at the very least it is possible to redistribute the gains that it creates to make workers—of different skill levels—better off. Labor market frictions change this picture. In the presence of such frictions, firms' automation decisions do not internalize the fact that the marginal product of labor is above its opportunity cost, or equivalently, do not recognize that there are first-order losses that workers will suffer as a result of automation. Consequently, equilibrium automation could reduce GDP and welfare and there may not be a way to make (all) workers better off, even with tools for costless redistribution. Under these circumstances, a utilitarian planner would choose a lower level of automation than the equilibrium.¹⁵

8.6 Concluding Remarks

Despite the growing concerns and intensifying debate about the implications of automation for the future of work, the economics profession and popular discussions lack a satisfactory conceptual framework. To us this

15. Naturally, if the planner could remove the rents, or the labor market frictions underpinning them, then the equilibrium would be restored to efficiency. Nevertheless, most sources of rents, including search, bargaining, and efficiency wages, would be present in the constrained efficient allocations as well.

lack of appropriate conceptual approach is also the key reason why much of the debate is characterized by a false dichotomy between the view that automation will spell the end of work for humans and the argument that technologies will always tend to increase the demand for labor as they have done in the past.

In this chapter, we summarized a conceptual framework that can help understand the implications of automation and bridge the opposite sides of this false dichotomy. At the center of our framework is a task-based approach, where automation is conceptualized as replacing labor in tasks that it used to perform. This type of replacement causes a direct displacement effect, reducing labor demand. If this displacement effect is not counterbalanced by other economic forces, it will reduce labor demand, wages, and employment. But our framework also emphasizes that there are several countervailing forces. These include the fact that automation will reduce the costs of production and thus create a productivity effect, the induced capital accumulation, and the deepening of automation—technological advances that increase the productivity of machines in tasks that have already been automated.

Our framework also emphasizes that these countervailing forces are generally insufficient to totally balance out the implications of automation. In particular, even if these forces are strong, the displacement effect of automation tends to cause a decline in the share of labor in national income. But we know from the history of technology and industrial development that despite several waves of rapid automation, the growth process has been more or less balanced, with no secular downward trend in the share of labor in national income. We argue this is because of another powerful force: the creation of new tasks in which labor has a comparative advantage, which fosters a countervailing reinstatement effect for labor. These tasks increase the demand for labor and tend to raise the labor share. When they go hand-in-hand with automation, the growth process is balanced and it need not imply a dismal scenario for labor.

Nevertheless, the adjustment process is likely to be slower and more painful than this account of balance between automation and new tasks at first suggests. This is because the reallocation of labor from its existing jobs and tasks to new ones is a slow process, in part owing to time-consuming search and other labor market imperfections. But even more ominously, new tasks require new skills. When the education sector does not keep up with the demand for new skills, the mismatch between skills and technologies is bound to complicate the adjustment process and hinder the productivity gains from new technologies.

Our framework further suggests that there are additional reasons for the productivity slowdown. At the center of these is a tendency for excessive automation because of the tax treatment of capital investments and labor market imperfections. Excessive automation directly reduces productivity,

but may have even more powerful indirect effects because it redirects technological improvements away from productivity-enhancing activities that lead to the creation of new tasks to excessive efforts at the extensive margin of automation, a picture that receives informal support from the current singular focus on AI and deep learning.

We would like to conclude by pointing out a number of additional issues that may be important in understanding the full impact of AI and other automation technologies on future prospects of labor. We believe that these issues can be studied using simple extensions of the framework presented here.

First, we have emphasized the role of the productivity effect in partially counterbalancing the displacement effect created by automation. However, this countervailing effect works by increasing the demand for products. As we have also seen, automation tends to increase inequality. If, as a consequence of this distributional impact, the rise in real incomes resulting from automation ends up in the hands of a narrow segment of the population with much lower marginal propensity to consume than those losing incomes and their jobs, these countervailing forces would be weakened and might operate much more slowly. This imbalance in the distribution of the gains from automation might slow down the creation of new tasks as well.

Second, our analysis highlighted the negative consequences of a shortage of skills for realizing the productivity gains from automation and for inequality. In practice, the problem may be workers acquiring the wrong types of skills rather than a general lack of skills. For example, if AI and other new automation technologies necessitate a mix of numeracy, communication, and problem-solving skills different than those emphasized in current curricula, this would have implications similar to those of a shortage of skills, but it cannot be overcome by just increasing educational spending with current educational practices remaining intact. One important consideration in this respect is that there is little concrete information about what types of skills new technologies will complement, underscoring the importance of further empirical work in this area.

Third, government policies and labor market institutions may impact not just the speed of automation (and thus whether there is excessive automation), but what types of technologies will receive more investments. To the extent that some uses of AI may complement labor more or generate opportunities for more rapid creation of new tasks, an understanding of the impact of various policies, including support for academic and applied research, and social factors on the path of development of AI is critical.

Last but not least, the development and adoption of technologies that reinstate labor cannot be taken for granted. If we do not find a way of creating shared prosperity from the productivity gains generated by new technologies, there is a danger that the political reaction to these technologies may slow down or even completely stop their adoption and development. This

underscores the importance of studying the distributional implications of AI and robotics, the political economy reactions to it, and the design of new and improved institutions for creating more broadly shared gains from these new technologies.

Appendix

Derivations for the Basic Model

Suppose that assumption (A1) holds. We first derive the demand for factors:

- Denote by $p(x)$ the price of task x . Assumption (A1) implies

$$(8A.1) \quad p(x) = \begin{cases} \frac{R}{\gamma_M(x)} & \text{if } x \in [N-1, I] \\ \frac{W}{\gamma_L(x)} & \text{if } x \in (I, N]. \end{cases}$$

- In addition, the demand for task x is given by

$$y(x) = \frac{Y}{p(x)}.$$

- Thus, the demand for smart machines in task x is

$$k(x) = \begin{cases} \frac{Y}{R} & \text{if } x \in [N-1, I] \\ 0 & \text{if } x \in (I, N] \end{cases},$$

and the demand for labor in task x is

$$\ell(x) = \begin{cases} 0 & \text{if } x \in [N-1, I] \\ \frac{Y}{W} & \text{if } x \in (I, N] \end{cases}.$$

- Aggregating the demand for machines from this expression and setting it equal to the supply of capital, K , we have the following market-clearing condition for capital:

$$K = \frac{Y}{R}(I - N + 1).$$

Similarly, aggregating the demand for labor and setting it equal to its inelastic supply, L , we obtain the market-clearing condition for labor as

$$L = \frac{Y}{W}(N - I).$$

- Rearranging these two equations, the equilibrium rental rate and wage can be obtained as

$$(8A.2) \quad R = \frac{Y}{K}(I - N + 1) \text{ and } W = \frac{Y}{L}(N - I),$$

which are the expressions used in the text.

We next turn to deriving the expression for aggregate output.

- Because we normalized the price of the final good to 1 as numeraire, we have

$$\int_{N-1}^N \ln p(x) dx = 0.$$

- Plugging in the expressions for $p(x)$ from equation (8A.1) yields

$$\int_{N-1}^I [\ln R - \ln \gamma_M(x)] dx + \int_I^N [\ln W - \ln \gamma_L(x)] dx = 0.$$

- Substituting the expressions for R and W from (8A.2), we obtain

$$\int_{N-1}^I [\ln Y - \ln(K/(I - N + 1)) - \ln \gamma_M(x)] dx + \int_I^N [\ln Y - \ln(L/(N - I)) - \ln \gamma_L(x)] dx = 0.$$

- This equation can be rearranged as

$$\begin{aligned} \ln Y &= \int_{N-1}^I \left[\ln \left(\frac{K}{I - N + 1} \right) + \ln \gamma_M(x) \right] dx + \int_I^N \left[\ln \left(\frac{L}{N - I} \right) + \ln \gamma_L(x) \right] dx \\ &= \int_{N-1}^I \ln \gamma_M(x) dx + \int_I^N \ln \gamma_L(x) dx \\ &\quad + (I - N + 1) \ln \left(\frac{K}{I - N + 1} \right) + (N - I) \ln \left(\frac{L}{N - I} \right), \end{aligned}$$

which, after taking exponentials on both sides of the equation, yields the expression for aggregate output in equation (1) in the text.

Assumption (A1)

We now show that assumption (A1) is equivalent to the capital-labor ratio of the economy taking an intermediate value. In particular, there exist two positive thresholds $\underline{k} < \bar{k}$ such that assumption (A1) holds whenever

$$(A2) \quad \frac{K}{L} \in (\underline{\kappa}, \bar{\kappa}).$$

Equation (8A.2) shows that

$$\frac{W}{R} = \frac{K}{L} \frac{N - I}{I - N + 1}.$$

Define

$$\underline{\kappa} = \frac{I - N + 1}{N - I} \frac{\gamma_L(I)}{\gamma_M(I)}, \text{ and } \bar{\kappa} = \frac{I - N + 1}{N - I} \frac{\gamma_L(N)}{\gamma_M(N - I)}.$$

Then equation (A2) is equivalent to assumption (A1).

Derivations in the Presence of Technology-Skill Mismatch

- Denote by $p(x)$ the price of task x . Assumption (A1) together with the fact that $W_H > W_L$ (see footnote 12) implies

$$p(x) = \begin{cases} \frac{R}{\gamma_M(x)} & \text{if } x \in [N - 1, I] \\ \frac{W_L}{\gamma_L(x)} & \text{if } x \in (I, S) \\ \frac{W_H}{\gamma_L(x)} & \text{if } x \in S, N] \end{cases} .$$

- Following the same steps as in our baseline model, we obtain the market-clearing condition for capital,

$$K = \frac{Y}{R}(I - N + 1).$$

- The demand for low-skill labor in task x is given by

$$\ell(x) = \begin{cases} 0 & \text{if } x \in [N - 1, I] \\ \frac{Y}{W_L} & \text{if } x \in (I, S) \\ 0 & \text{if } x \in S, N]. \end{cases} .$$

- Aggregating the demand for low-skill labor and setting it equal to its inelastic supply, L , we obtain the market-clearing condition for low-skill labor as

$$L = \frac{Y}{W_L}(S - I),$$

which implies the expression for W_L given in the main text.

- The demand for high-skill labor in task x is given by

$$h(x) = \begin{cases} 0 & \text{if } x \in [N-1, I] \\ 0 & \text{if } x \in (I, S) \\ \frac{Y}{W_H} & \text{if } x \in S, N]. \end{cases}$$

- Aggregating the demand for high-skill labor and setting it equal to its supply, H , we obtain the market-clearing condition for high-skill labor as

$$H = \frac{Y}{W_H}(N - S),$$

which implies the expression for W_H given in the main text.

Derivations for the Model with Distortions

- Denote by $p(x)$ the price of task x . The variant of assumption (A1) introduced in section 8.5 implies

$$p(x) = \begin{cases} \frac{R(1-\tau)}{\gamma_M(x)} & \text{if } x \in [N-1, I] \\ \frac{W(1+\omega)}{\gamma_L(x)} & \text{if } x \in (I, J) \\ \frac{W}{\gamma_L(x)} & \text{if } x \in J, N]. \end{cases}$$

- Following the same steps as in the model with no distortions, we obtain the market-clearing condition for capital,

$$K = \frac{Y}{R(1-\tau)}(I - N + 1).$$

- The demand for labor in task x is

$$\ell(x) = \begin{cases} 0 & \text{if } x \in [N-1, I] \\ \frac{Y}{W(1+\omega)} & \text{if } x \in (I, J) \\ \frac{Y}{W} & \text{if } x \in J, N] \end{cases}.$$

- The expression for $\ell(x)$ implies that the total amount of labor employed in tasks where labor gets rents is

$$L_A = \frac{Y}{W(1+\omega)}(J - I).$$

The total amount of labor employed in tasks where labor does not get rents is

$$L - L_A = \frac{Y}{W} (N - J).$$

To derive the expression for (gross) output we proceed as follows:

- Again from our choice of numeraire, we have

$$\int_{N-1}^N \ln p(x) dx = 0.$$

- Plugging in the expressions for $p(x)$ we obtain

$$\begin{aligned} \int_{N-1}^I \left[\ln R - \ln \gamma_M(x) \right] dx + \int_I^J \left[\ln W + \ln(1 + \omega) - \ln \gamma_L(x) \right] dx \\ + \int_J^N \left[\ln W - \ln \gamma_L(x) \right] dx = 0. \end{aligned}$$

- Substituting for factor prices using the expressions for K , L_A , and $L - L_A$, we obtain

$$\begin{aligned} \int_{N-1}^I \left[\ln Y - \ln \left(K / (I - N + 1) \right) - \ln \gamma_M(x) \right] dx \\ + \int_I^J \left[\ln Y - \ln \left(L_A / (J - I) \right) - \ln \gamma_L(x) \right] dx \\ + \int_I^J \left[\ln Y - \ln \left((L - L_A) / (N - J) \right) - \ln \gamma_L(x) \right] dx = 0. \end{aligned}$$

- This equation can be rearranged as

$$\begin{aligned} \ln Y &= \int_{N-1}^I \left[\ln \left(\frac{K}{I - N + 1} \right) + \ln \gamma_M(x) \right] dx + \int_I^J \left[\ln \left(\frac{L_A}{J - I} \right) + \ln \gamma_L(x) \right] dx \\ &+ \int_J^N \left[\ln \left(\frac{L}{N - J} \right) + \ln \gamma_L(x) \right] dx \\ &= \int_{N-1}^I \ln \gamma_M(x) dx + \int_I^N \ln \gamma_L(x) dx + (I - N + 1) \ln \left(\frac{K}{I - N + 1} \right) \\ &+ (J - I) \ln \left(\frac{L_A}{J - I} \right) + (N - J) \ln \left(\frac{L - L_A}{N - J} \right), \end{aligned}$$

which yields equation (12) in the text.

References

- Accenture PLC. 2017. "How Companies Are Reimagining Business Processes With IT." <https://sloanreview.mit.edu/article/will-ai-create-as-many-jobs-as-it-eliminates/>.
- Acemoglu, Daron. 2009. *Introduction to Modern Economic Growth*. Princeton, NJ: Princeton University Press.
- Acemoglu, Daron, and David Autor. 2011. "Skills, Tasks and Technologies: Implications for Employment and Earnings." *Handbook of Labor Economics* 4:1043–171.
- Acemoglu, Daron, David Autor, David Dorn, Gordon H. Hanson, and Brendan Price. 2014. "Return of the Solow Paradox? IT, Productivity, and Employment in US Manufacturing." *American Economic Review: Papers & Proceedings* 104 (5): 394–99.
- Acemoglu, Daron, and Pascual Restrepo. 2016. "The Race between Machine and Man: Implications of Technology for Growth, Factor Shares and Employment." *American Economic Review* 108 (6): 1488–542.
- . 2017. "Robots and Jobs: Evidence from US Labor Markets." NBER Working Paper no. 23285, Cambridge, MA.
- . 2018a. "Excessive Automation: Technology Adoption and Worker Displacement in a Frictional World." Unpublished manuscript.
- . 2018b. "Low-Skill and High-Skill Automation." *Journal of Human Capital* 12 (2): 204–32.
- Aghion, Philippe, Benjamin F. Jones, and Charles I. Jones. 2017. "Artificial Intelligence and Economic Growth." NBER Working Paper no. 23928, Cambridge, MA.
- Allen, Robert C. 2009. "Engels' Pause: Technical Change, Capital Accumulation, and Inequality in the British Industrial Revolution." *Explorations in Economic History* 46 (4): 418–35.
- American Enterprise Institute (AEI). 2008. "Taxing Capital." Report by the American Enterprise Institute. <https://www.aei.org>.
- Autor, David H. 2015. "Why Are There Still So Many Jobs? The History and Future of Workplace Automation." *Journal of Economic Perspectives* 29 (3): 3–30.
- Autor, David H., David Dorn, and Gordon H. Hanson. 2013. "The China Syndrome: Local Labor Market Effects of Import Competition in the United States." *American Economic Review* 103 (6): 2121–68.
- Autor, David H., Frank Levy, and Richard J. Murnane. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." *Quarterly Journal of Economics* 118 (4): 1279–333.
- Ayres, Robert, and Steven M. Miller. 1983. *Robotics: Applications and Social Implications*. Pensacola, FL: Ballinger Publishing Company.
- Bessen, James. 2016. *Learning by Doing: The Real Connection between Innovation, Wages, and Wealth*. New Haven, CT: Yale University Press.
- Bloom, Nicholas, Charles I. Jones, John Van Reenen, and Michael Webb. 2017. "Are Ideas Getting Harder to Find?" NBER Working Paper no. 23782, Cambridge, MA.
- Boston Consulting Group. 2015. "The Robotics Revolution: The Next Great Leap in Manufacturing." <https://www.bcg.com/en-us/publications/2015/lean-manufacturing-innovation-robotics-revolution-next-great-leap-manufacturing.aspx>.
- Brynjolfsson, Erik, and Andrew McAfee. 2014. *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. New York: W. W. Norton & Company.

- Chandler, Alfred D. 1977. *The Visible Hand: The Managerial Revolution in American Business*. Cambridge, MA: Harvard University Press.
- Deloitte and The Manufacturing Institute. 2011. "Boiling Point? The Skills Gap in U.S. Manufacturing." Report. <http://www.themanufacturinginstitute.org/~media/A07730B2A798437D98501E798C2E13AA.ashx>.
- Ford, Martin. 2016. *The Rise of the Robots: Technology and the Threat of a Jobless Future*. New York: Basic Books.
- Goldin, Claudia, and Larry Katz. 2010. *The Race between Education and Technology*. Cambridge, MA: Harvard University Press.
- Gordon, Robert J. 2016. *The Rise and Fall of American Growth: The U.S. Standard of Living Since the Civil War*. Princeton, NJ: Princeton University Press.
- Graetz, Georg, and Guy Michaels. 2015. "Robots at Work." CEP Discussion Paper no. 1335, Centre for Economic Performance.
- Groover, Mikell. 1983. *CAD/CAM: Computer-Aided Design and Manufacturing*. Englewood Cliffs, NJ: Prentice Hall.
- Groover, Mikell, Mitchell Weiss, Roger N. Nagel, and Nicholas G. Odrey. 1986. *Industrial Robotics: Technology, Programming and Applications*. New York: McGraw-Hill.
- Herrendorf, Berthold, Richard Rogerson, and Ákos Valentinyi. 2013. "Two Perspectives on Preferences and Structural Transformation." *American Economic Review* 103 (7): 2752–89.
- Kolb, David A. 1984. *Experiential Learning: Experience as the Source of Learning and Development*. Englewood Cliffs, NJ: Prentice Hall.
- Kuznets, Simon. 1966. *Modern Economic Growth*. New Haven, CT: Yale University Press.
- Landes, David. 1969. *The Unbound Prometheus*. New York: Cambridge University Press.
- Mantoux, Paul. 1928. *The Industrial Revolution in the Eighteenth Century: An Outline of the Beginnings of the Modern Factory System in England*. New York: Harcourt.
- Manuelli, Rodolfo E., and Ananth Seshadri. 2014. "Frictionless Technology Diffusion: The Case of Tractors." *American Economic Review* 104 (4): 1368–91.
- McKinsey Global Institute. 2017. "Jobs Lost, Jobs Gained: Workforce Transitions in a Time of Automation." Report, McKinsey & Company. <https://www.mckinsey.com/mgi/overview/2017-in-review/automation-and-the-future-of-work/jobs-lost-jobs-gained-workforce-transitions-in-a-time-of-automation>.
- Mian, Atif, and Amir Sufi. 2014. "What Explains the 2007–2009 Drop in Employment?" *Econometrica* 82 (6): 2197–223.
- Minsky, Marvin. 1967. *Computation: Finite and Infinite Machines*. Englewood Cliffs, NJ: Prentice-Hall.
- Mokyr, Joel. 1990. *The Lever of Riches: Technological Creativity and Economic Progress*. New York: Oxford University Press.
- Nilsson, Nils J. 2009. *The Quest for Artificial Intelligence: A History of Ideas and Achievements*. Cambridge: Cambridge University Press.
- Olmstead, Alan L., and Paul W. Rhode. 2001. "Reshaping the Landscape: The Impact and Diffusion of the Tractor in American Agriculture, 1910–1960." *Journal of Economic History* 61 (3): 663–98.
- Pew Research Center. 2017. "Automation in Everyday Life." Online Report. <http://www.pewinternet.org/2017/10/04/automation-in-everyday-life/>.
- Rasmussen, Wayne D. 1982. "The Mechanization of Agriculture." *Scientific American* 247 (3): 76–89.
- Simon, Herbert A. 1965. *The Shape of Automation for Men and Management*. New York: Harper & Row.

- Syverson, Chad. 2017. "Challenges to Mismeasurement Explanations for the US Productivity Slowdown." *Journal of Economic Perspectives* 31 (2): 165–86.
- Tuzel, Selale, and Miao Ben Zhang. 2017. "Economic Stimulus at the Expense of Routine-Task Jobs." Unpublished manuscript, Marshall School of Business, University of Southern California.
- Zeira, Joseph. 1998. "Workers, Machines, and Economic Growth." *Quarterly Journal of Economics* 113 (4): 1091–117.

Contributors

Daron Acemoglu
Department of Economics
Massachusetts Institute of
Technology
50 Memorial Drive
Cambridge, MA 02142-1347

Philippe Aghion
Collège de France
3 Rue D'Ulm
75005 Paris, France

Ajay Agrawal
Rotman School of Management
University of Toronto
105 St. George Street
Toronto, ON M5S 3E6, Canada

Susan Athey
Graduate School of Business
Stanford University
655 Knight Way
Stanford, CA 94305

James Bessen
Technology & Policy Research
Initiative
Boston University School of Law
765 Commonwealth Avenue
Boston, MA 02215

Erik Brynjolfsson
MIT Sloan School of Management
100 Main Street, E62-414
Cambridge, MA 02142

Colin F. Camerer
Department of Economics
California Institute of Technology
1200 East California Boulevard
Pasadena, CA 91125

Judith Chevalier
Yale School of Management
135 Prospect Street
New Haven, CT 06520

Iain M. Cockburn
School of Management
Boston University
595 Commonwealth Avenue
Boston, MA 02215

Tyler Cowen
Department of Economics
George Mason University
4400 University Drive
Fairfax, VA 22030

Patrick Francois
Vancouver School of Economics
University of British Columbia
IONA Building, 6000 Iona Drive
Vancouver, BC V6T 2E8, Canada

Jason Furman
Harvard Kennedy School
79 John F. Kennedy Street
Cambridge, MA 02138

Alberto Galasso
Rotman School of Management
University of Toronto
105 St. George Street
Toronto, ON M5S 3E6, Canada

Joshua Gans
Rotman School of Management
University of Toronto
105 St. George Street
Toronto, ON M5S 3E6, Canada

Avi Goldfarb
Rotman School of Management
University of Toronto
105 St. George Street
Toronto, ON M5S 3E6, Canada

Austan Goolsbee
University of Chicago Booth School
of Business
5807 S. Woodlawn Avenue
Chicago, IL 60637

Rebecca Henderson
Harvard Business School
Morgan Hall 445
Soldiers Field Road
Boston, MA 02163

Ginger Zhe Jin
Department of Economics
University of Maryland
3115F Tydings Hall
College Park, MD 20742-7211

Benjamin F. Jones
Department of Management and
Strategy
Kellogg School of Management
Northwestern University
2211 Campus Drive
Evanston, IL 60208

Charles I. Jones
Graduate School of Business
Stanford University
655 Knight Way
Stanford, CA 94305-4800

Daniel Kahneman
Woodrow Wilson School
Princeton University
Princeton, NJ 08544-1013

Anton Korinek
University of Virginia
Monroe Hall 246
248 McCormick Road
Charlottesville, VA 22904

Mara Lederman
Rotman School of Management
University of Toronto
105 St. George Street
Toronto, Ontario M5S 3E6, Canada

Hong Luo
Harvard Business School
Morgan Hall 241
Soldiers Field Road
Boston, MA 02163

John McHale
108 Cairnes Building
School of Business and Economics
National University of Ireland
Galway H91 TK33, Ireland

Paul R. Milgrom
Department of Economics
Stanford University
579 Serra Mall
Stanford, CA 94305-6072

Matthew Mitchell
Rotman School of Management
University of Toronto
105 St. George Street
Toronto, ON M5S 3E6, Canada

Alexander Oettl
Scheller College of Business
Georgia Institute of Technology
800 West Peachtree Street NW
Atlanta, GA 30308

Andrea Prat
Columbia Business School
Uris Hall 624
3022 Broadway
New York, NY 10027-6902

Manav Raj
Stern School of Business
New York University
44 West Fourth Street
New York, NY 10012

Pascual Restrepo
Department of Economics
Boston University
270 Bay State Road
Boston, MA 02215

Daniel Rock
MIT Sloan School of Management
100 Main Street, E62-365
Cambridge, MA 02142

Jeffrey D. Sachs
Center for Sustainable Development,
Earth Institute
Columbia University
535 West 116th Street, MC 4327
New York, NY 10027

Robert Seamans
Stern School of Business
New York University
44 West 4th Street, KMC 7-58
New York, NY 10012

Scott Stern
MIT Sloan School of Management
100 Main Street, E62-476
Cambridge, MA 02142

Betsy Stevenson
Gerald R. Ford School of Public Policy
University of Michigan
5224 Weill Hall
735 South State Street
Ann Arbor, MI 48109-3091

Joseph E. Stiglitz
Columbia University
Uris Hall 212
3022 Broadway
New York, NY 10027

Chad Syverson
University of Chicago Booth School of
Business
5807 S. Woodlawn Avenue
Chicago, IL 60637

Matt Taddy
University of Chicago Booth School of
Business
5807 S. Woodlawn Avenue
Chicago, IL 60637

Steven Tadelis
Haas School of Business
University of California, Berkeley
545 Student Services Building
Berkeley, CA 94720

Manuel Trajtenberg
Eitan Berglas School of Economics
Tel Aviv University
Tel Aviv 69978, Israel

Daniel Trefler
Rotman School of Management
University of Toronto
105 St. George Street
Toronto, ON M5S 3E6, Canada

Catherine Tucker
MIT Sloan School of Management
100 Main Street, E62-536
Cambridge, MA 02142

Hal Varian
School of Information
University of California, Berkeley
102 South Hall
Berkeley, CA 94720-4600

Author Index

- 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
Aguilar, M., 386n36
Airoldi, 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
Crisuolo, 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
 Durantón, 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
İsçan, 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
 Karabarounis, 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
 Künzel, 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-Llopolis, 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

Subject Index

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, technologies and, 26–28
- AI. *See* artificial intelligence (AI)
- AlphaGo (Google), 63
- Amazon Go concept, 67
- applied artificial intelligence, 208
- artificial intelligence (AI), 1; and automation 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; economies 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 participation 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 productivity 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 technology (GPT) era: education strategies for, 179–82; human-enhancing innovations 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 intelligence, 62f, 63–65
 double machine learning, 523–24
- economic growth: artificial intelligence and, 262–70; prospects for technology-driven, 149–53; Zeira model of automation 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 outside 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 Accountability Act of 1996 (HIPAA), 454
 HEI (human-enhancing innovations), 184–85
 heterogeneous treatment effects, 524–28
 hierarchical Poisson factorization, 510
 HIPAA. *See* Health Insurance Portability 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 intelligence in, 250–52
 implementation/restructuring lags, as explanation 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