Adapting to Technological Change with Artificial Intelligence

Council of Economic Advisers

July 29, 2019

Introduction

- In fiction & reality, technological change has often been viewed with alarm
  - In Greek mythology, Prometheus was punished for bringing fire to mortals
  - In early 1800s, Luddites attempted to destroy textile mills and automated machine looms
  - In the Terminator movies, the AI system Skynet wages war on humanity
- Economic evidence & reasoning provides a more nuanced view of AI's impact
  - Capital and labor responses can yield gains from specialization based on comparative advantage
  - The labor market effects will be uneven across occupations and industries
  - Although there will be disruptions, eventually AI will improve labor productivity and living standards

AI definition

- "machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments. It uses machine and/or human-based inputs to perceive real and/or virtual environments; abstract such perceptions into models (in an automated manner e.g. with ML or manually); and uses model inference to formulate options for information or action. AI systems are designed to operate with varying levels of autonomy." (*Artificial Intelligence in Society*, OECD 2019).
- Machine-learning is integral to AI
  - Supervised learning algorithms "learn" relationships between descriptive variables and outcome variables
  - Unsupervised learning algorithms detect patterns in the data
  - Reinforcement learning algorithms use an objective function that specifies how the system responds to its environment under arbitrary degrees of stochasticity
  - Deep learning algorithms, which may be supervised or unsupervised, use many-layered neural networks for complex tasks such as image identification. Much of the modern fundamental breakthroughs in machine vision, translation, etc. have been driven by machine learning

Examples: AI applications in healthcare

- Primary categories of AI in the medical field are machine learning and natural language processing
  - Machine learning (ML) analyzes structured data to group patients based on traits and predict the probabilities of health outcomes
  - Natural Language Processing (NLP), a class of machine learning algorithms dedicated towards understanding language, extracts supplemental data from unstructured data such as clinical notes or medical journals, classifies text by topic, identifies sentiment, and more.
- Detection, Diagnosis, Prediction
  - The most successful AI applications have been used for early detection of disease and probabilities of outcomes for cancer, neurology, cardiology, and strokes
  - Example: AI systems involved in early diagnosis of stroke using neuroimaging techniques led to earlier care and better health outcomes

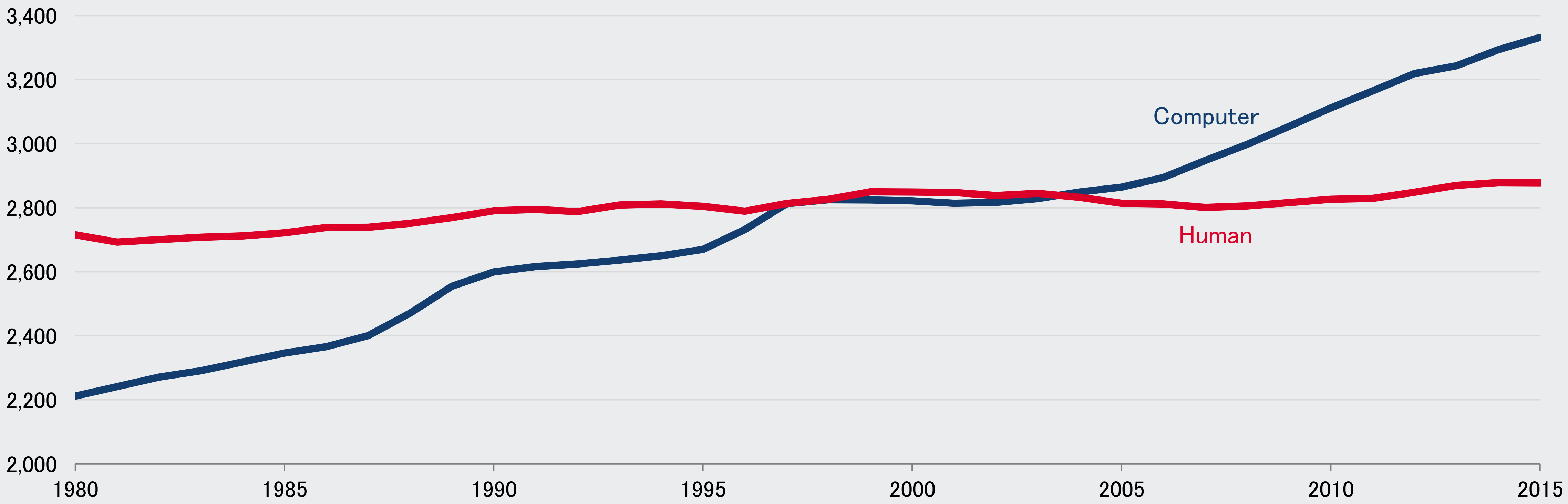
Will AI replace human labor?

- AI performing existing tasks more efficiently and new tasks that were traditionally viewed as infeasible
- AlphaZero defeated the world's best chess engine, StockFish
  - DeepBlue used human-built logic-based system to defeat Gary Kasparov in 1997
  - AlphaZero uses deep-learning reinforcement algorithms
- Under certain conditions, AI can classify images more reliably than humans
  - Algorithms can still be tricked by savvy programmers using methods such as adversarial images
  - AI's dominance in games such as Chess, Go, and Starcraft is driven by the ease of collecting large amounts of data from the sealed environment

AI plays chess better than humans

A Measure of Chess Playing Competency, 1980–2015

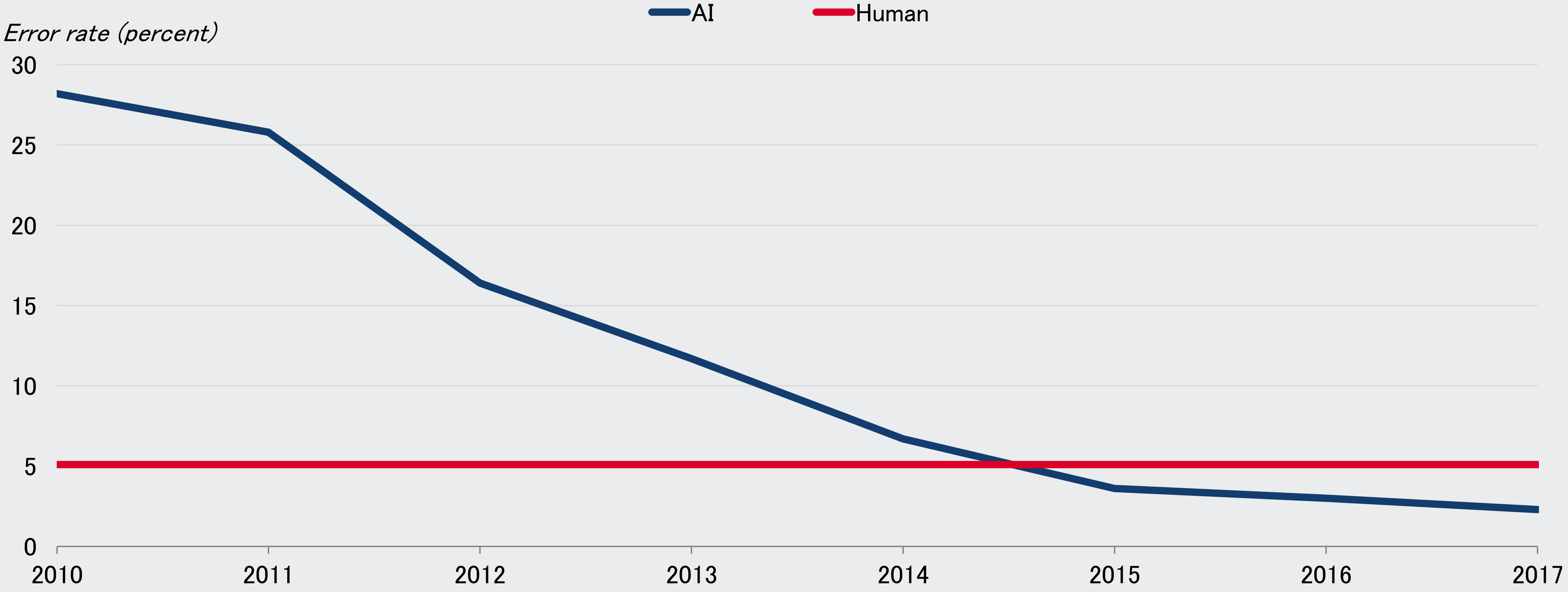
Elo score



Source: National Academies (2017).
Note: An Elo score measures competency in competitive games.

AI classifies images better than humans

Error Rate of Image Processing, 2010–17



Source: Russakovsky et al. (2015); CEA calculations.

Trade between people and machines

- Gains from trade when humans specialize in tasks where humans have a comparative advantage over machines
- In capital investments, designing machines that complement rather than substitute for humans will be more profitable
  - "Human-in-the-Loop Reinforcement Learning"
- Where labor is scarce, AI and robots that take the place of humans will be more profitable
- In the labor market, workers are drawn to jobs and tasks that are more difficult to automate
  - Even though they might consult "Dr. Google," in survey data, most patients prefer human healthcare workers

Uneven effects of technological change

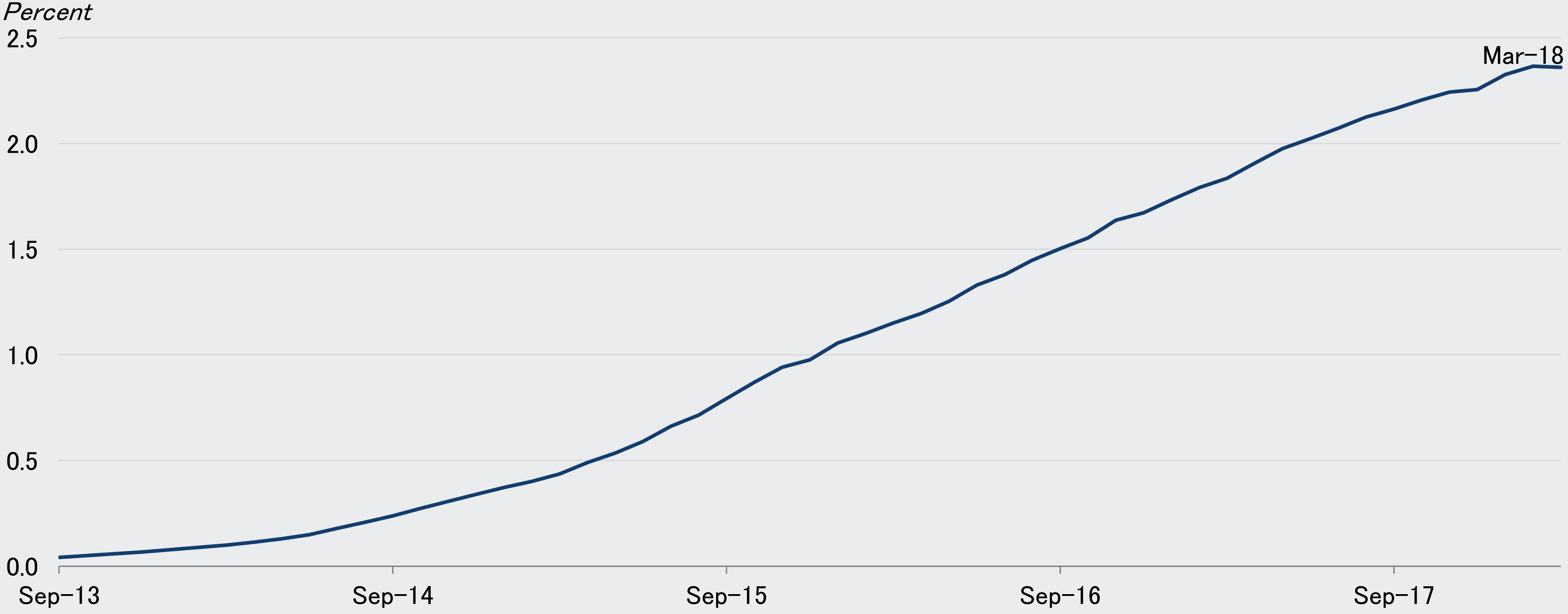
- "Skill-biased technological change:" more complementarity between technology and higher-skilled workers
- Factor-substitution and scale effects determine the net impact of technological change on labor demand in an industry
  - Over the 20th Century, the agricultural sector substituted capital for labor: the agricultural employment share dropped from 41% to 2%
  - Scale effect: production costs fell, prices fell, and agricultural output increased
  - But demand for agricultural output is relatively price-inelastic
  - So the factor-substitution effect dominated the scale effect

Technology can increase labor demand

- When demand is relatively elastic, scale effect can dominate factor–substitution effect
- Technological innovation: smartphone apps substitute for taxicab dispatchers
  - Ridesharing services generated large gains in consumer surplus
  - Employment in the passenger transportation sector expanded (however average wages dropped)
  - When even newer technology –– autonomous vehicles – is adopted, employment might drop again

Technology increased employment in personal transportation sector

Employment Share of Ridesharing Platforms, 2013–18



Source: J.P. Morgan Chase (2018).

Technological change improves life

National Academy of Sciences (2017): *Information Technology and the U.S. Workforce: Where Are We and Where Do We Go from Here?*

- "Productivity is the key driver of increased living standards. In turn, innovation, diffusion, or adoption of technology is the key driver of improvements in productivity. The most important technology of this era is IT."
- "However, the existence of technology alone is not enough to enhance productivity. Effective use of technology typically requires a shift toward complementary skills profiles in the workforce and adaptation of business processes, organization of work, and institutional processes. These changes can be costly and take decades to play out."

Phases of adjustment to AI

- Anticipation phase: businesses begin to switch to activities that are intensive in cognitive tasks, but AI is not yet adequate to perform those tasks
- Implementation phase: AI arrives
  - Real wages may fall as machines compete with workers
- Long-run: business formation catches up with the new technology as they identify opportunities for value generation and labor usage
  - Real wages are higher

Labor productivity trends in the US and Japan

Labor Productivity Growth in the U.S. and Japan, 1990–2018

Sources: OECD; U.S. Bureau of Labor Statistics; CEA calculations.

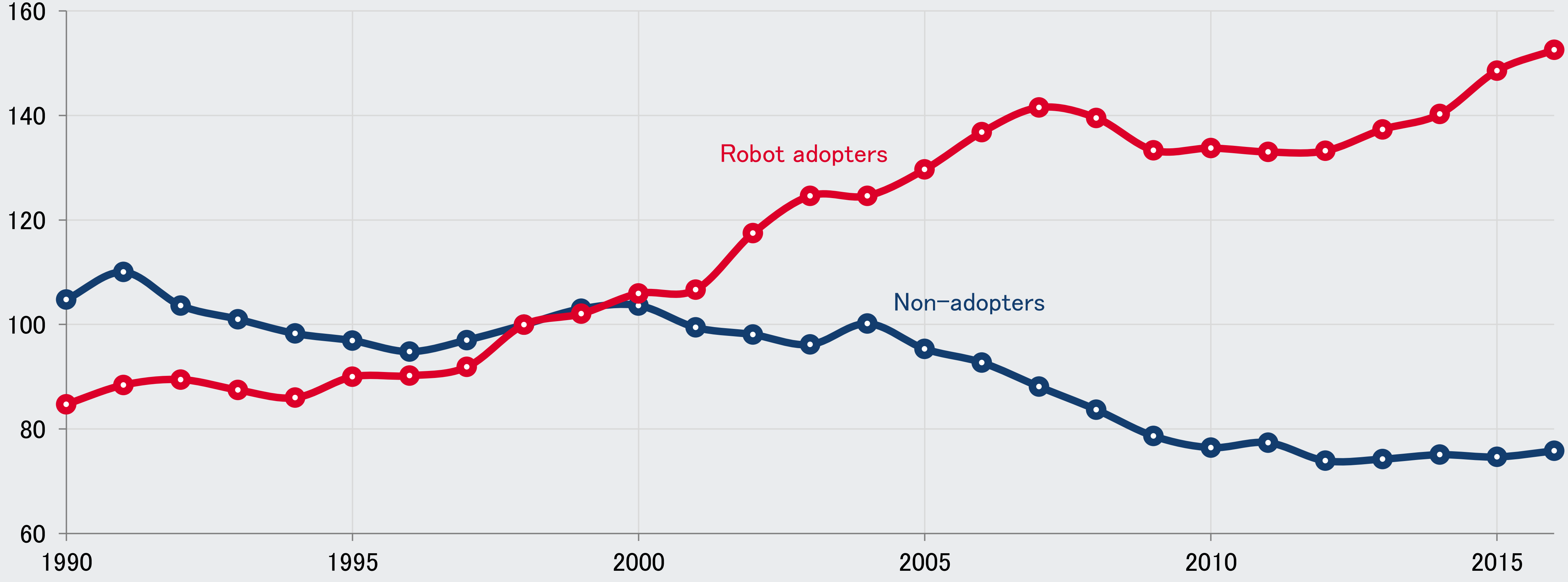
Slowdown in productivity

- U.S. productivity growth was 3.2 percent between 1995 and 2004 and slowed to 1.3 percent from 2004 to 2014
- Similar slowdown in productivity across advanced economies in Europe and in Japan (Baily and Montalbano 2016)
- Why haven't AI investments improved labor productivity?
  - AI's contributions might not be fully measured
  - Trial and error process takes a while before productivity benefits are fully realized
- Total factor productivity (TFP) remains stable in Japan and is increasing in the U.S.

Firms that adopted robots 1990–1998 increased human employment 1998–2016

Evolution of Firm-Level Employment, 1990–2016

Number of workers (Indexed, 1998 = 100)



Source: Koch, Manuylov, and Smolka (2019).

References

CEA (Council of Economic Advisors). 2019. *Economic Report of the President.* Washington: U.S. Government Publishing Office. https://www.whitehouse.gov/wp-content/uploads/2019/03/ERP-2019.pdf.

JPMorgan Chase. 2018. "The Online Platform Economy in 2018: Drivers, Workers, Sellers, and Lessors." https://www.jpmorganchase.com/corporate/institute/document/institute-ope-2018.pdf.

Jiang, F., Y. Jiang, H. Zhi, Y. Dong, H. Li, S. Ma, Y. Wang, Q. Dong, H. Shen, and Y. Wang. 2017. "Artificial Intelligence in Healthcare: Past, Present and Future." *Stroke and Vascular Neurology* 2, no. 4: 230–243.

Koch, M., Manuylov, I., and M. Smolka. 2019. "Robots and Firms." *CESIFO Working Papers*, no. 7608.

National Academies. 2017. *Information Technology and the U.S. Workforce: Where Are We and Where Do We Go from Here?* Report of National Academies of Sciences, Engineering, and Medicine, Committee on Information Technology, Automation, and the U.S. Workforce. Washington: National Academies Press.

Russakovsky, O., J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein, A. Berg, and L. Fei-Fei. 2015. "ImageNet Large Scale Visual Recognition Challenge." *International Journal of Computer Vision* 115, no. 3: 211–52.