Acemoglu Discussion

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Acemoglu-Restrepo Approach

- Innovation at task level involves taking a task and substituting a person for a machine
- AI/Automation could be welfare reducing
  - If the **displacement effect** outweighs the **productivity effect**
  - Possible for ‘so-so' AI innovations rather than ‘brilliant’ ones
  - Counterbalanced by **reinstatement effect** (new tasks)
- Empirical exercise: forecast these effects
  - Past changes in labour share appear to be driven by change in **task composition** (displacement)
  - Magnified **distortions** from subsidies to capital and costs of labour
- Policy response
  - Use government to change the **direction** of AI research
  - Away from human-replacement and towards human-augmentation

General Equilibrium

$$Y = wL + (1 + r)K$$

General equilibrium condition:

$$\underset{\substack{\uparrow \\ \text{Labour} \\ \text{Requirement}}}{wa} + (1 + r)\underset{\substack{\uparrow \\ \text{Capital} \\ \text{Requirement}}}{b} = 1$$

New technique:

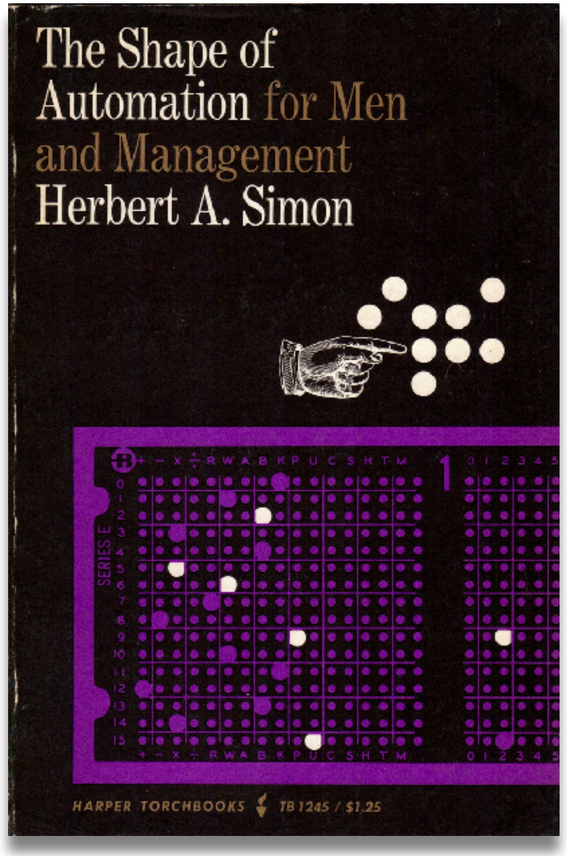
$$wa' + (1 + r)b' < 1$$

$$\implies w' > w$$

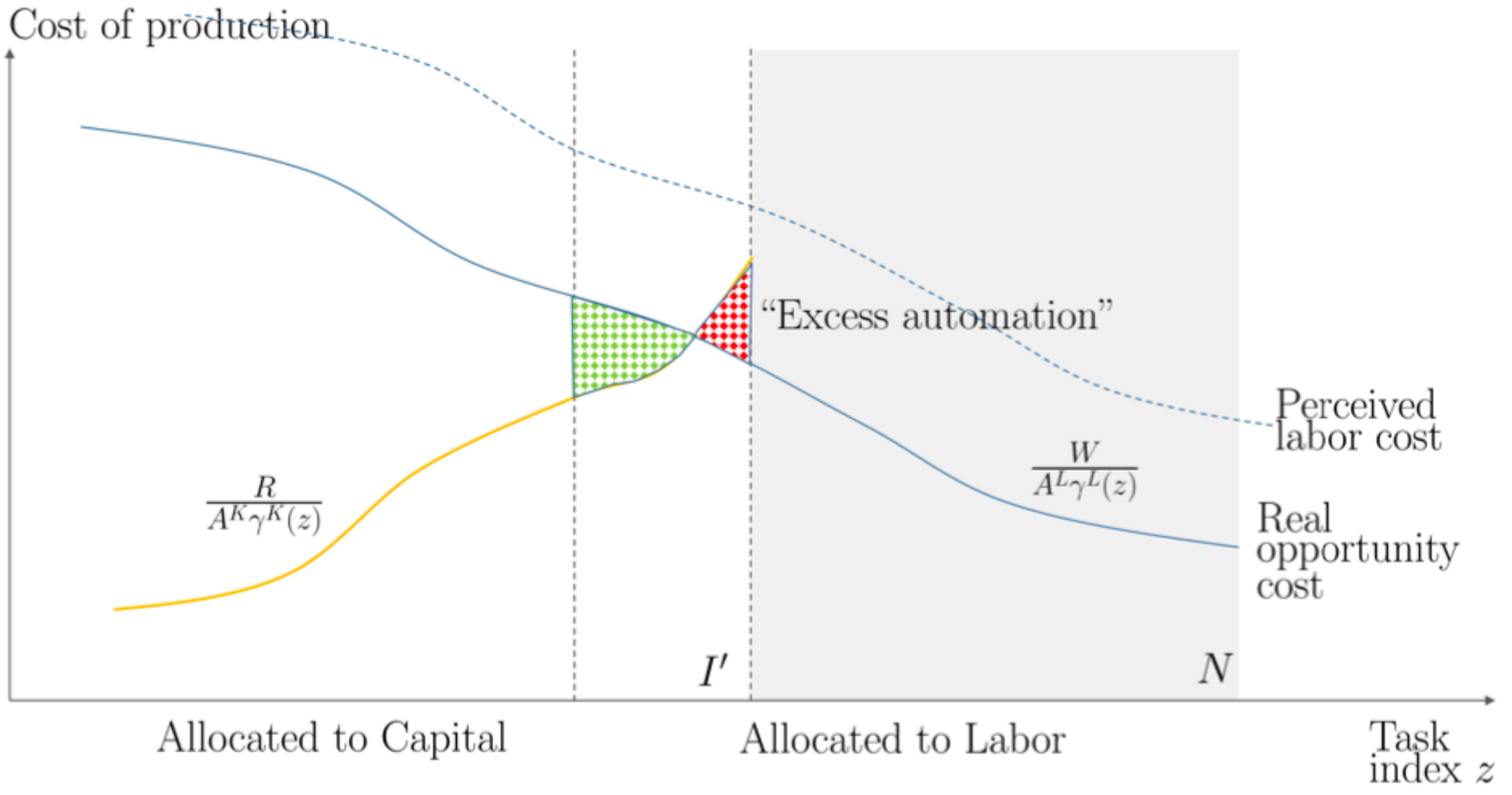
Lower wages requires:

$$wa + (1 + r)b' > 1$$

$$\implies b' > b$$



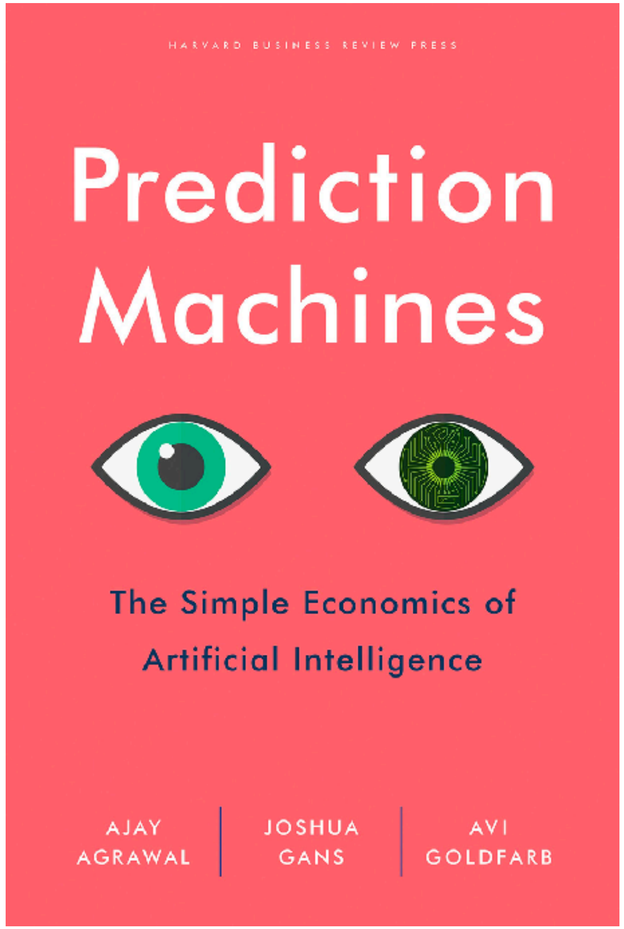
Welfare harm is related to incentives to develop/adopt inefficient production techniques

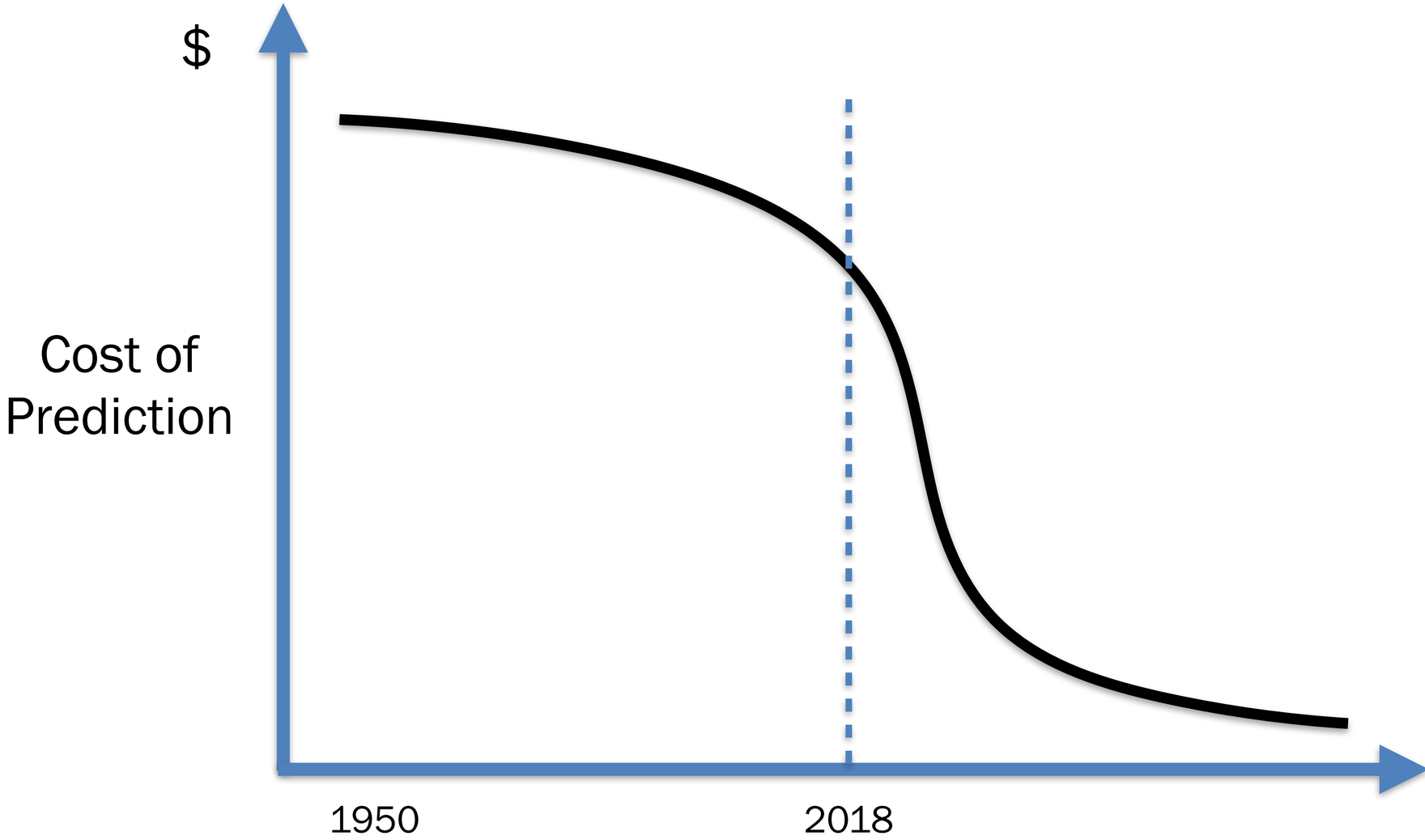

Cost of production
"Excess automation"
Perceived labor cost
$\frac{W}{A^L\gamma^L(z)}$
Real opportunity cost
$\frac{R}{A^K\gamma^K(z)}$
I'
N
Allocated to Capital
Allocated to Labor
Task index z

Will adopted AI involve less efficient production?

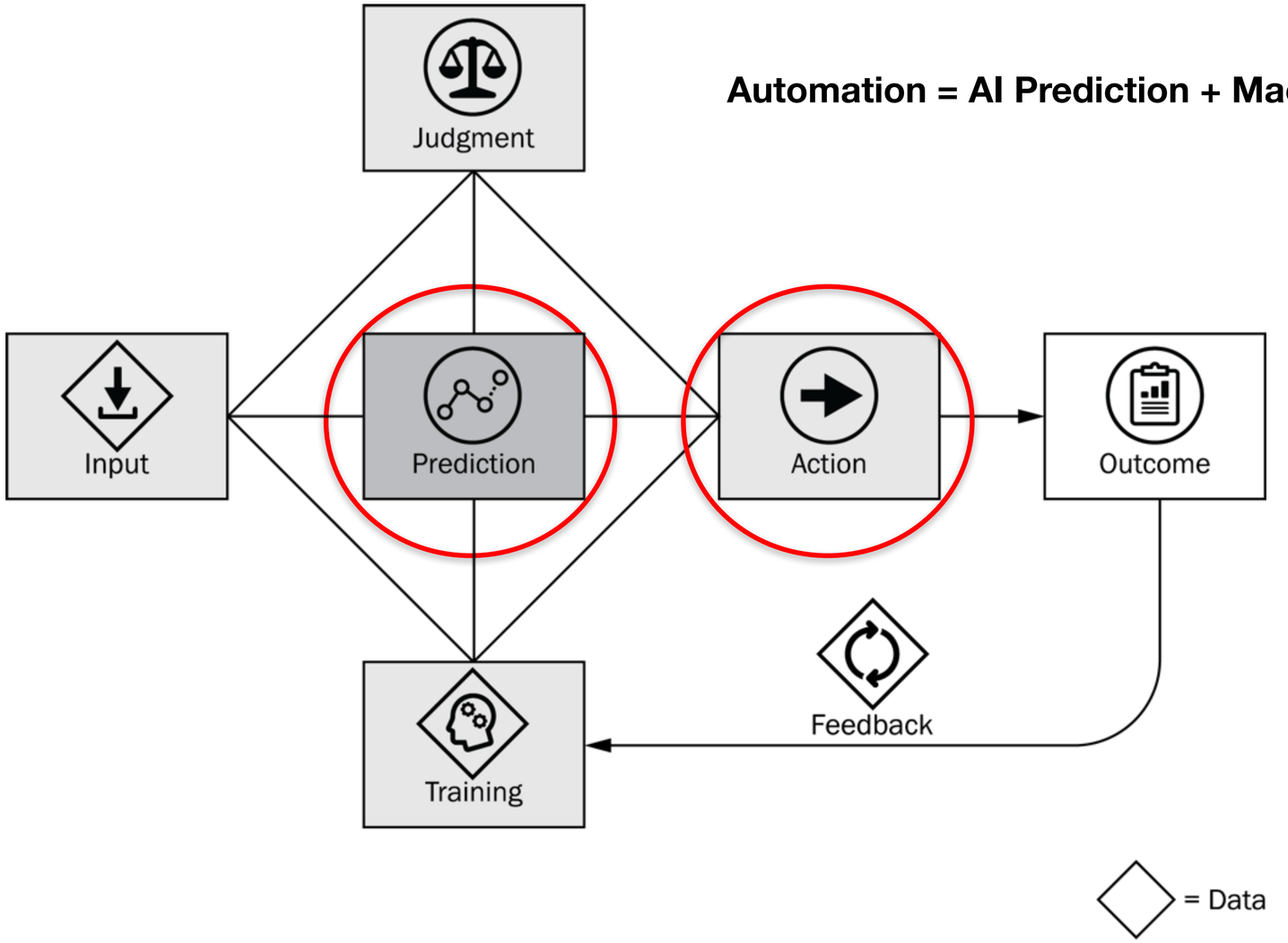
Good Automation?

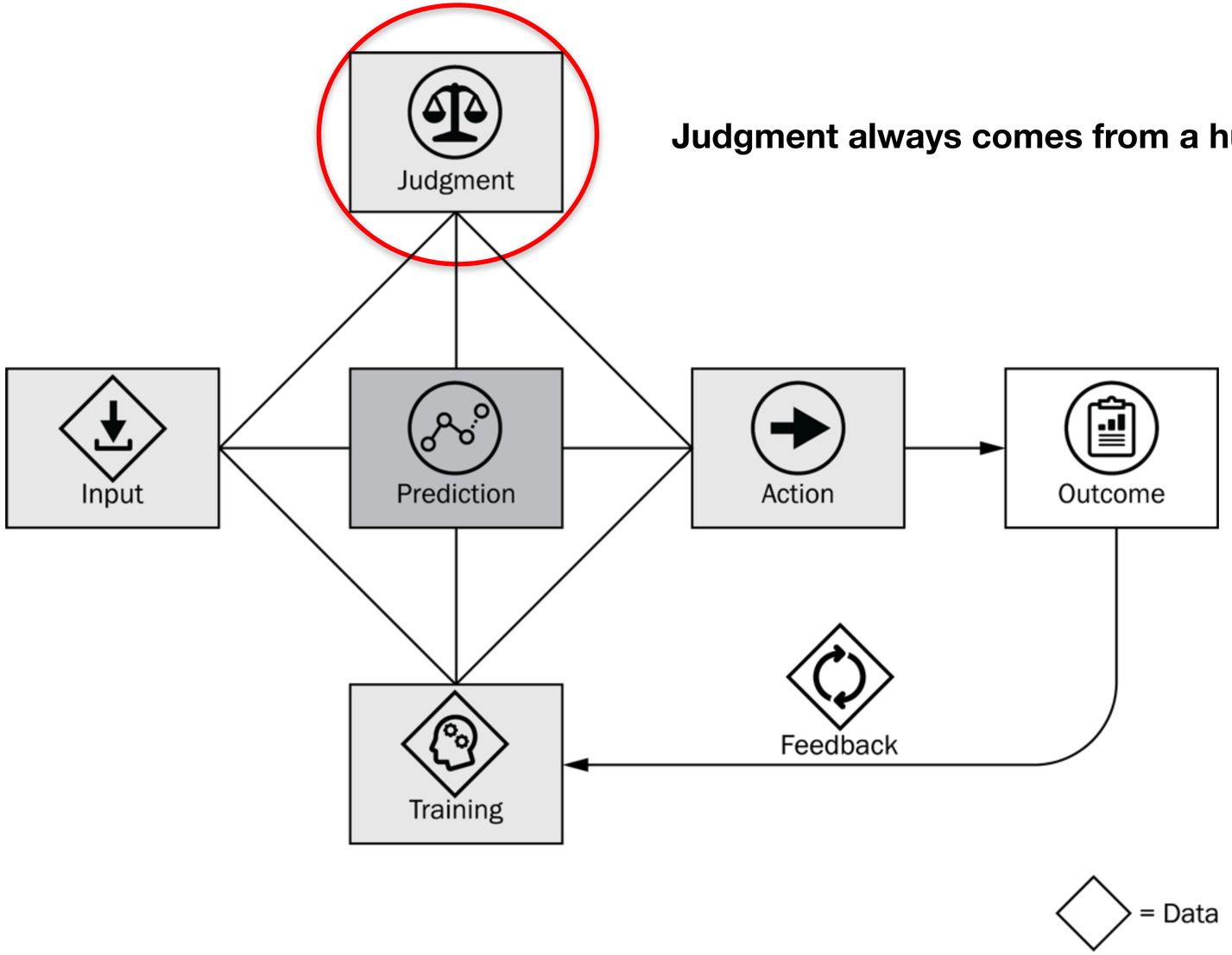
AI vs. Automation





Automation = AI Prediction + Machine Action





Judgment always comes from a human

AI provides Prediction

Automation includes both Prediction + Action

Hard-Coded Judgment

Automation requires Judgment at Scale

Lower complexity?

Innovation: take task and add AI

- If judgment in-moment — augments human
- If judgment hard-coded — full substitution

implies … pure wage to capital price driven involves centralised judgment
where judgment also coded, productivity driven.

3

Prediction, Judgment, and Complexity

A Theory of Decision-Making and Artificial Intelligence

Ajay Agrawal, Joshua Gans, and Avi Goldfarb

3.1 Introduction

There is widespread discussion regarding the impact of machines on employment (see Autor 2015). In some sense, the discussion mirrors a long-standing literature on the impact of the accumulation of capital equipment on employment; specifically, whether capital and labor are substitutes or complements (Acemoglu 2003). But the recent discussion is motivated by the integration of software with hardware and whether the role of machines goes beyond physical tasks to mental ones as well (Brynjolfsson and McAfee 2014). As mental tasks were seen as always being present and essential, human comparative advantage in these was seen as the main reason why, at least in the long term, capital accumulation would complement employment by enhancing labor productivity in those tasks.

The computer revolution has blurred the line between physical and men-

System-Level Substitution

AI Adoption and System-Wide Change

Ajay Agrawal, Joshua S. Gans, Avi Goldfarb

May 2021

Abstract

Analyses of AI adoption focus on its adoption at the individual task level. What has received significantly less attention is how AI adoption is shaped by the fact that organisations are composed of many interacting tasks. AI adoption may, therefore, require system-wide change which is both a constraint and an opportunity. We provide the first formal analysis where multiple tasks may be part of a modular or non-modular system. We find that reliance on AI, a prediction tool, increases decision variation which, in turn, raises challenges if decisions across the organisation interact. Modularity, which leads to task independence rather than system-level inter-dependencies, softens that impact. Thus, modularity can facilitate AI adoption. However, it does this at the expense of synergies. By contrast, when there are mechanisms for inter-decision coordination, AI adoption is enhanced when there is a non-modular environment. Consequently, we show that there are important cases where AI adoption will be enhanced when it can be adopted beyond tasks but as part of a designed organisational system.

Keywords: artificial intelligence, machine learning, modularity, systems

- Empirical forecasts based on forensic examination of tasks miss key organisational level decisions
- If AI adoption requires system change, it will be slower but also involve more labour than task-level analyses suggest
- System-level change can, when it kicks in, be very disruptive
- Focus on speed of displacement.

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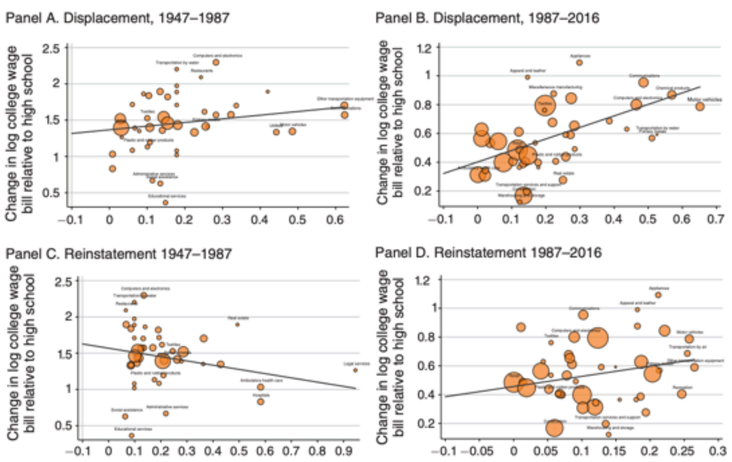
https://doi.org/10.1257/pandp.20201063

Unpacking Skill Bias: Automation and New Tasks†

By Daron Acemoglu and Pascual Restrepo*



The Impact of Artificial Intelligence on the Labor Market

Michael Webb*

Stanford University

January 2020

Latest version: https://web.stanford.edu/~mww/webb_jmp.pdf

Table 3: **Occupations with highest and lowest exposure to robots.**

Most exposed occupations	Least exposed occupations
Forklift driver	Payroll and timekeeping clerks
Operating engineers of cranes, derricks, etc.	Art/entertainment performers
Elevator installers and repairers	Clergy
Janitors	Correspondence and order clerks
Locomotive operators: engineers and firemen	Eligibility clerks for government programs

Notes: Table displays census occupation title for the five occupations with the highest exposure scores and with the lowest exposure scores above employment threshold of 150.

AEA Papers and Proceedings 2018, 108: 43–47
https://doi.org/10.1257/pandp.20181019

ECONOMIC CONSEQUENCES OF ARTIFICIAL INTELLIGENCE AND ROBOTICS‡

What Can Machines Learn and What Does It Mean for Occupations and the Economy?†

By Erik Brynjolfsson, Tom Mitchell, and Daniel Rock*

Rapid advances in machine learning (ML) or surpass humans in certain types of tasks,

Table 2—Lowest and Highest 5 SML Score Occupations

Low SML occupations	SML	High SML occupations	SML
Massage therapists	2.78	Concierges	3.9
Animal scientists	3.09	Mechanical drafters	3.9
Archeologists	3.11	Morticians, undertakers, and funeral directors	3.89
Public address system and other announcers	3.13	Credit authorizers	3.78
Plasterers and stucco masons	3.14	Brokerage clerks	3.78

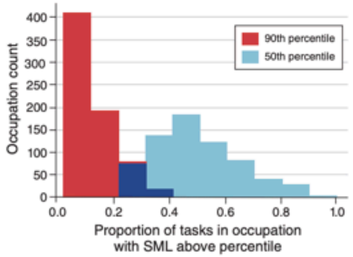
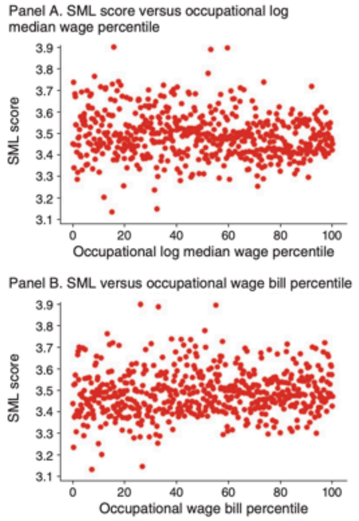


Figure 1. Frequency Counts of Occupational Task Proportions Above Ninetieth, Seventy-fifth, and Fiftieth Percentiles



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Technological Forecasting & Social Change

The future of employment: How susceptible are jobs to computerisation?☆

Carl Benedikt Frey[a,*], Michael A. Osborne[b]

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ABSTRACT

We examine how susceptible jobs are to computerisation. To assess this, we begin by implementing a novel methodology to estimate the probability of computerisation for 702 detailed occupations, using a Gaussian process classifier. Based on these estimates, we examine expected impacts of future computerisation on US labour market outcomes, with the primary objective of analysing the number of jobs at risk and the relationship between an occupations probability of computerisation, wages and educational attainment.

Linking Advances in Artificial Intelligence to Skills, Occupations, and Industries

Edward W. Felten, Manav Raj, and Robert Seamans[1]

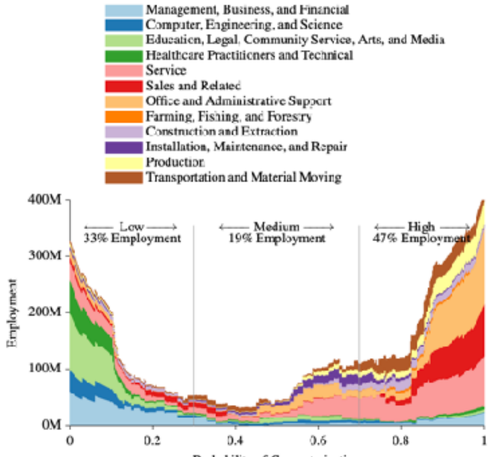
Draft: December 21, 2017

Table 2— Most and Least Impacted Occupations by EFF Historical AI Progress

	Most Impacted		Least Impacted	
	Occupations	Scheduled Definition	Occupations	Scheduled Definition
1	Airline Pilots, Copilots, and Flight Engineers	✓	Models	
2	Physicians		Telemarketers	
3	Surgeons	✓	Locker Room, Coatroom, and Dressing Room	
4	Commercial Pilots	✓	Graders and Sorters, Agricultural Products	
5	Air Traffic Controllers		Shampooers	
6	Dentists, General		Maids and Housekeeping Cleaners	
7	Biochemists and Biophysicists		Cleaners of Vehicles and Equipment	
8	Oral and Maxillofacial Surgeons		Slaughterers and Meat Packers	
9	First-Line Supervisors of Fire Fighting and Prevention Workers		Dining Room and Cafeteria Attendants and Bartender Helpers	
10	Microbiologists		Food Servers, Nonrestaurant	

Notes: Impact measured by constructed employment effect scores. Occupations as listed by the O*NET database.

Source: EFF; O*NET; BLS.



Tasks vs. Systems

Task View

- Labour has an absolute advantage in more complex tasks
- As AI becomes cheaper, less complex tasks are conducted by machines rather than labour
- This reduces the relative price of labour, which makes it economic to develop/add more complex tasks

System View

- Tasks are more productive when coordinated
- As AI becomes cheaper, tasks in modular systems are conducted by machines rather than labour
- This reduces the relative price of labour, which makes it economic to develop/add more labour to achieve coordination.

The difference is in whether factor choice is directed at cost minimisation or whether adoption is driven by what the technology can do. Will prices guide change or will function guide change?

Conclusions

- When an innovator is working on bringing AI to a task, what is motivating them?
- Are they motivated by saving labour costs?
  - If so, they are likely to be frustrated unless judgment is or can be hard-coded
  - If so, the costs may be higher than expected if the organisation isn’t modular
- Are they motivated by productivity/value?
  - If so, more innovative directions. Can focus on better prediction.
- Which is more likely?