The Transformative Power of AI: Uses and Applications of a New General-Purpose Technology

Kristina McElheran, University of Toronto

European Central Bank Conference on
The Transformative Power of AI: Economic Implications and Challenges

April 1st, 2025

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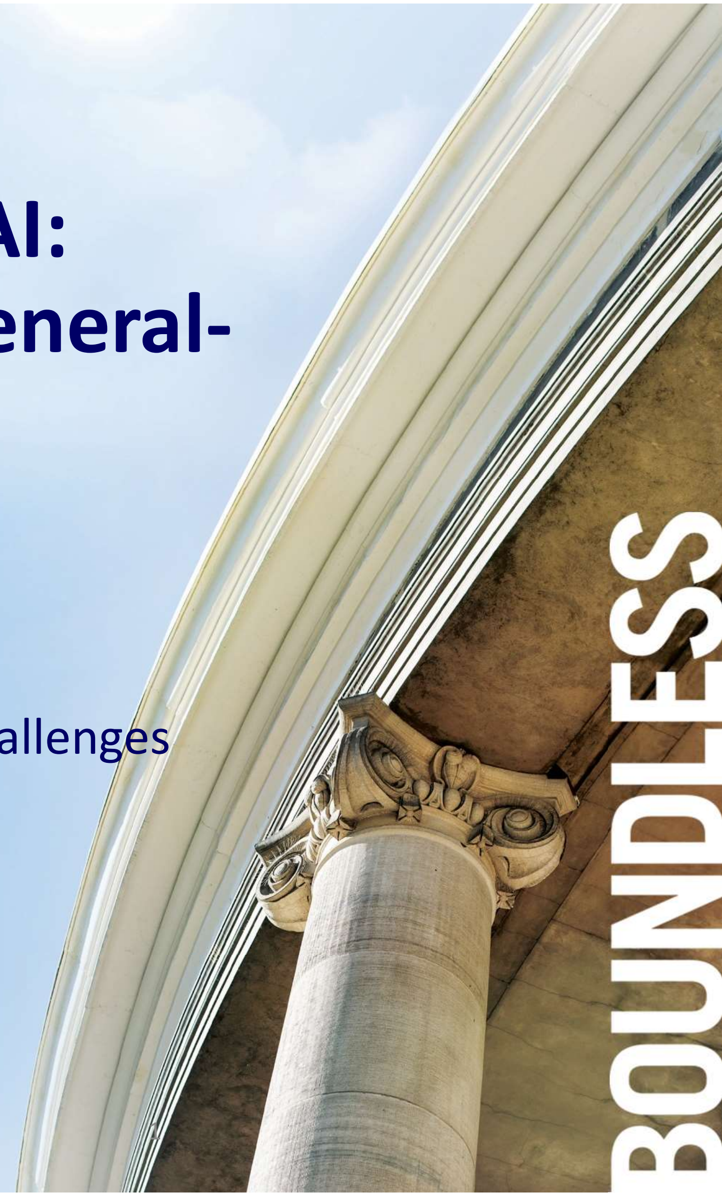
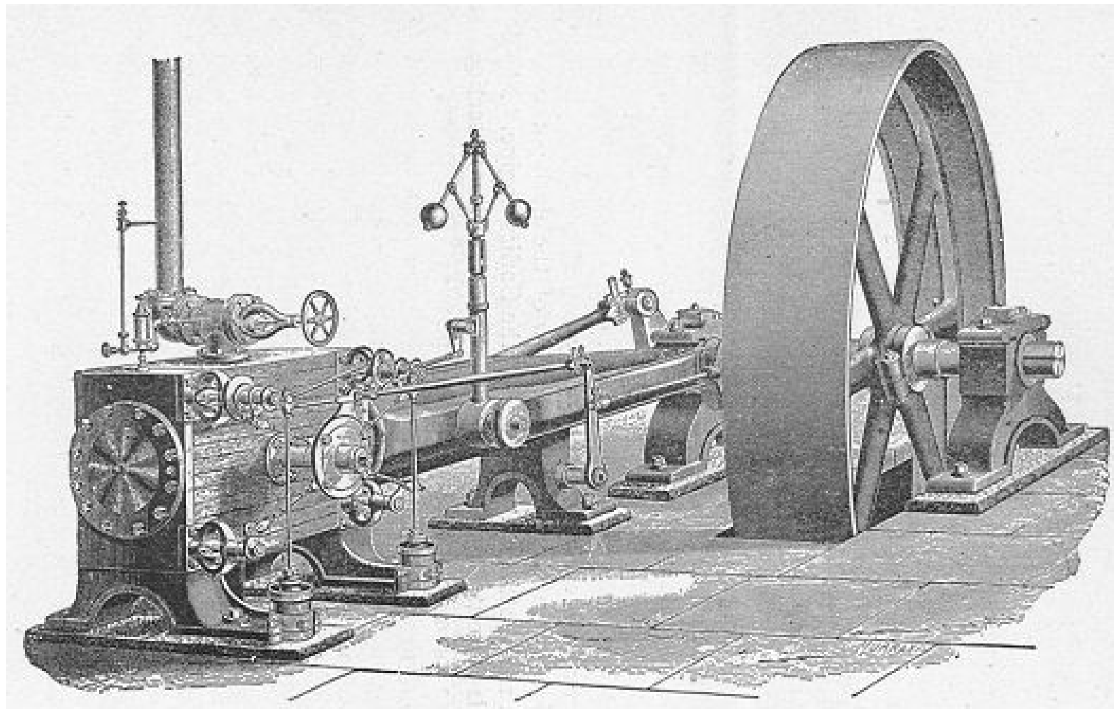


Remember this?



A Corliss Steam Engine – the symbol of the Centennial Exhibition in Philadelphia 1876

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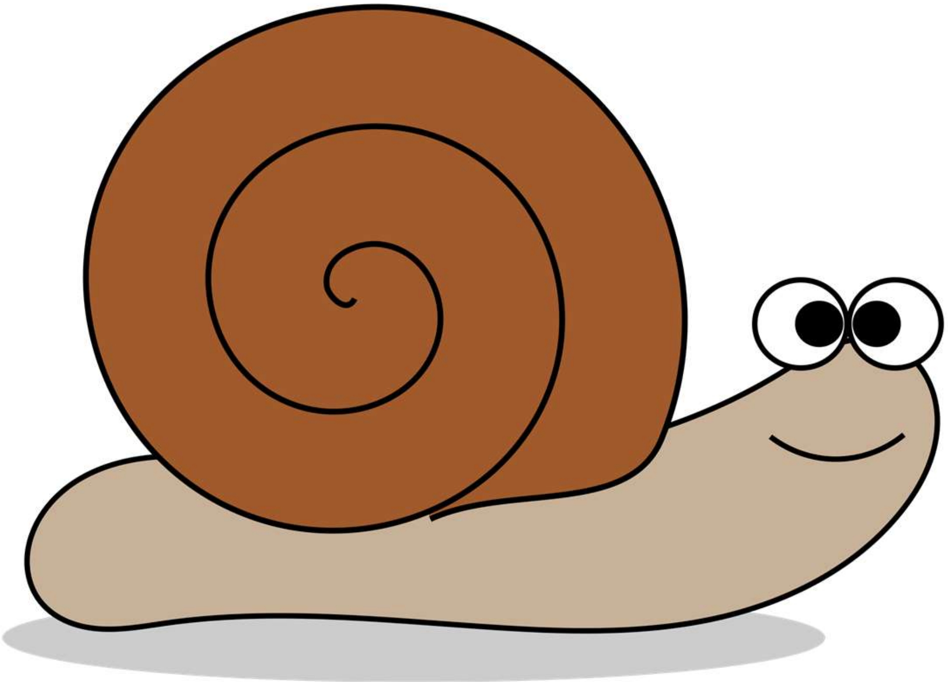
The Pace of Organizational Change



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One Reason = Human Nature & Cognitive Biases

https://www.kristinamcelheran.com/news-posts/data-analytics-from-bias-to-better-decisions

DATA ANALYTICS:
From Bias to Better Decisions

Data can be a highly effective decision-making tool. But it can also make us complacent. Leaders need to be aware of three common pitfalls.

by Megan MacGarvie and Kristina McElheran

https://store.hbr.org/product/data-analytics-from-bias-to-better-decisions/ROT367?srsltid=AfmBOorabRPmpIBAORnY1K_dK39b6MxZhW6QecWw9rGtLgtjtnP1N9Dq

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Linearity Bias in Humans (and Human-Composed Organizations)

Simple, Attractive, and Wrong: An Introduction to Linearity Bias

Author:
Will Goodrum

Date Published:
November 2, 2018

HARVARD BUSINESS REVIEW

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Decision Making And Problem Solving

Linear Thinking in a Nonlinear World

The obvious choice is often wrong. by Bart de Langhe, Stefano Puntoni and Richard Larrick

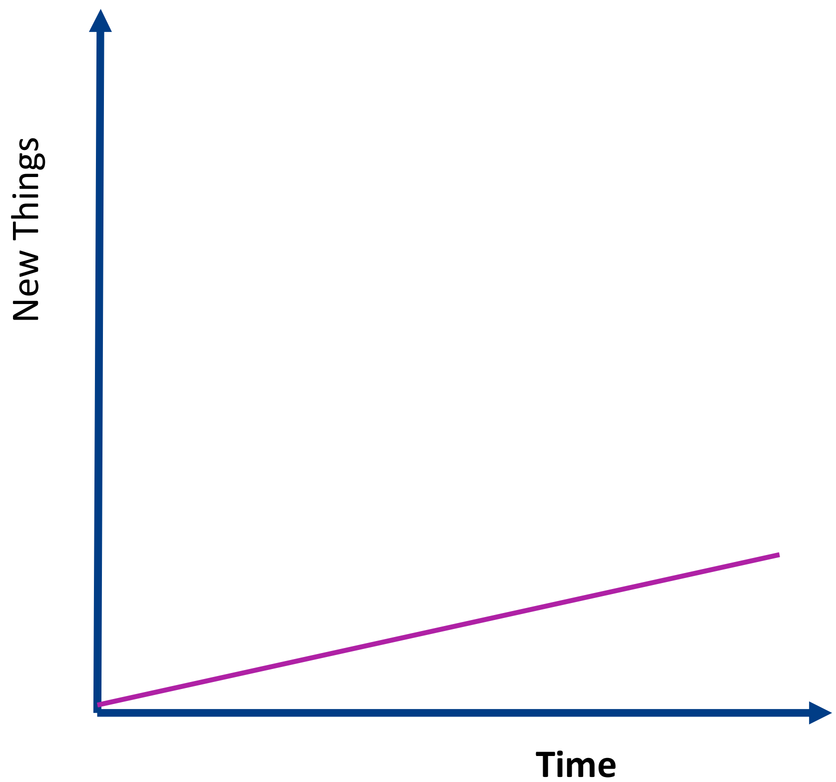
From the Magazine (May–June 2017)

Data Science

What is Linear Bias and why is it prominent in our day-to-day lives?

Sources:
- http://www.elderresearch.com/blog/simple-attractive-and-wrong-an-introduction-to-linearity-bias/
- http://hbr.org/2017/05/linear-thinking-in-a-nonlinear-world
- https://towardsai.net/p/data-science/linearity-bias

→ Organizational Change over Time



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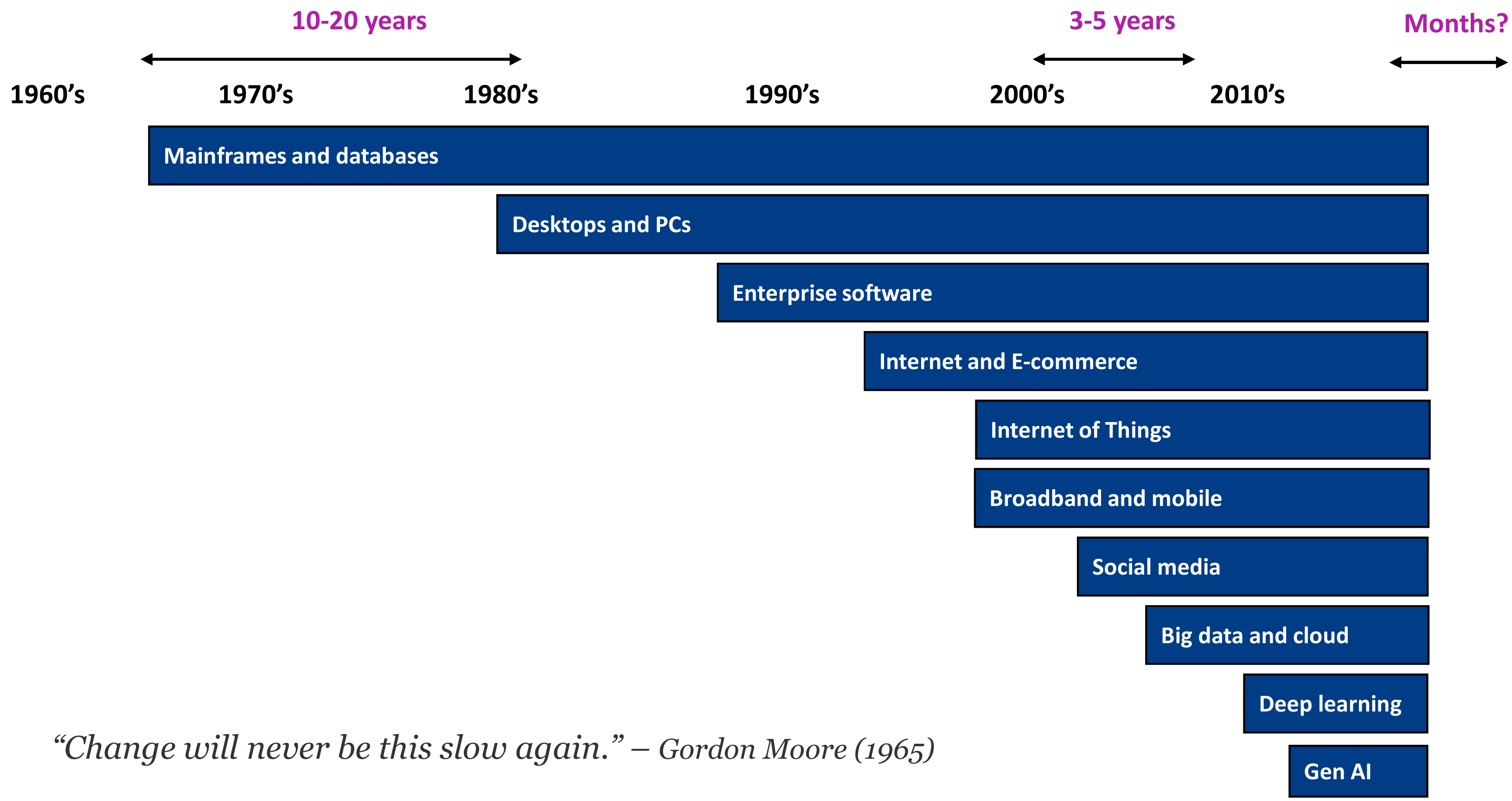
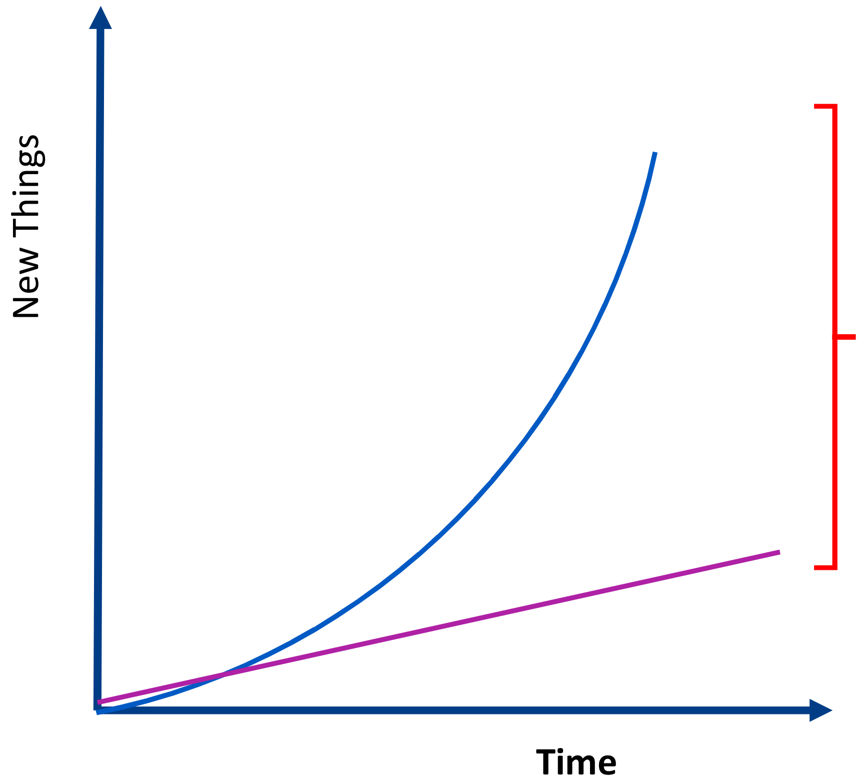
VS. THE PACE OF TECHNOLOGICAL CHANGE



"Change will never be this slow again." – Gordon Moore (1965)

Exponential Meets Linear Growth



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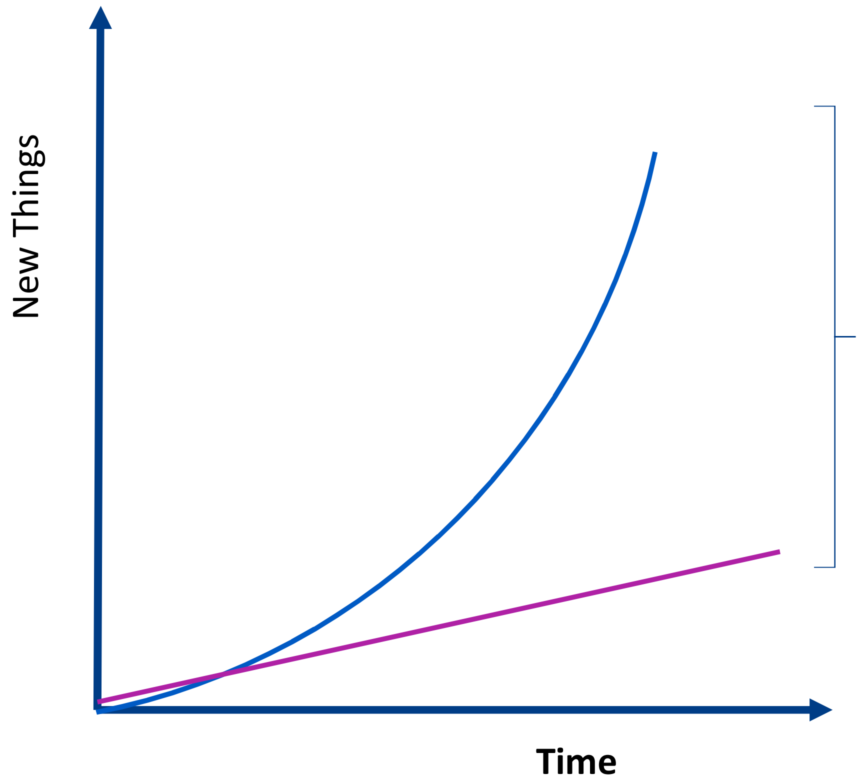
Exponential Meets Linear Growth



How to close the gap?

1. Facts > Hype
2. Attend to Co-Invention
3. Weather the J-Curve

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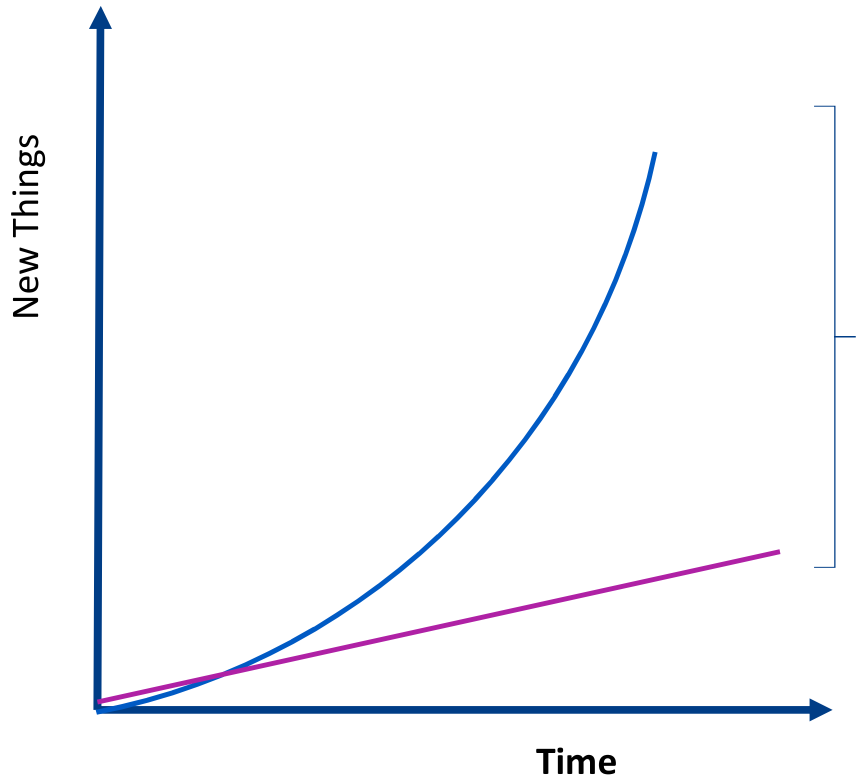
Exponential Meets Linear Growth



How to close the gap?

1. Facts > Hype

AI Adoption in America:
Who, What, and Where

Kristina McElheran®
J. Frank Li®
Erik Brynjolfsson®
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Emin Dinlersoz®
Lucia Foster®
Nikolas Zolas®

https://doi.org/10.1111/jems.12576
January 24, 2024

STANFORD DIGITAL ECONOMY LAB

2018 Annual Business Survey

1. Census Bureau Survey of **850,000** firms across the US to identify early adopters of AI and their key characteristics
   - Approximately 590,000 firms responded. **573,000** linked to Longitudinal Business Database (LBD)

2. Novel technology module
   - Digitization, cloud, advanced business technologies, including five key AI technologies.

3. Hard-to-measure organizational "intangibles"
   - Subsample of 75,000 startups
   - Owner characteristics, motivation, innovation strategies, business financing, etc.

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EARLY AI ADOPTION IN AMERICA:

- **LOW**
- **SKEWED**
- **VARIED**
- **CONCENTRATED**

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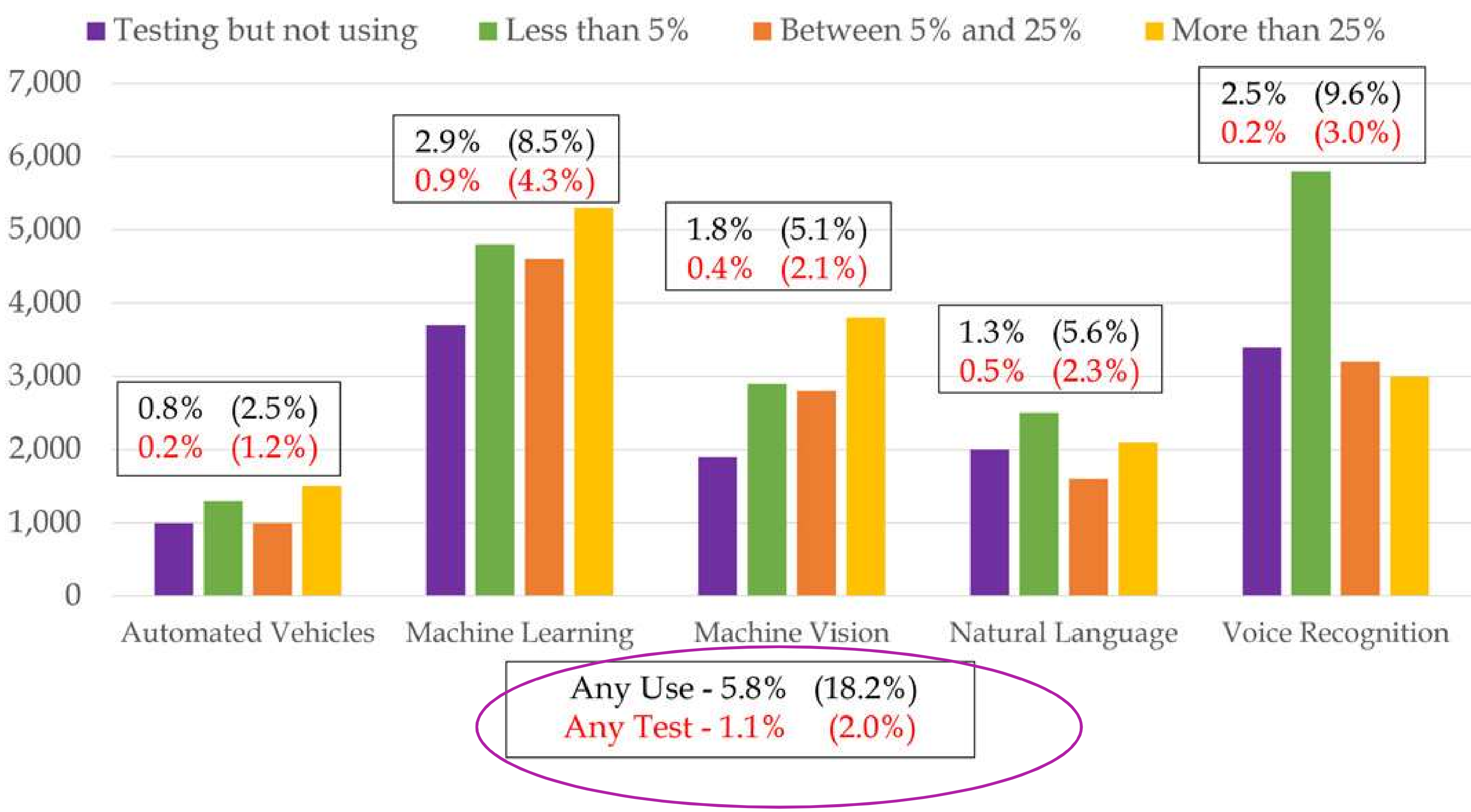
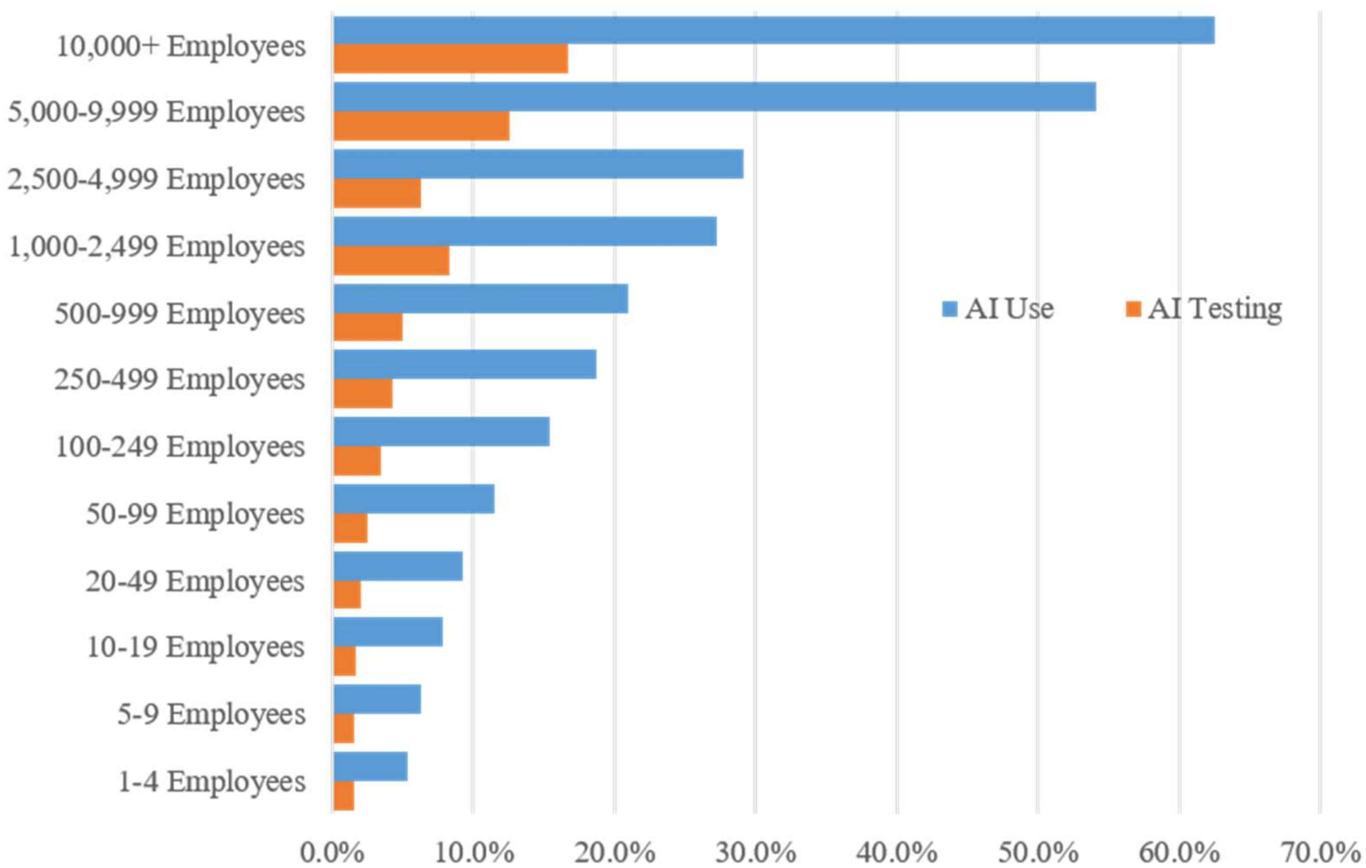
Representative Adoption Statistics:

ABS Responses to AI-Based Business Technologies (2017)



Only a very small percentage of respondents use **any** of these technologies

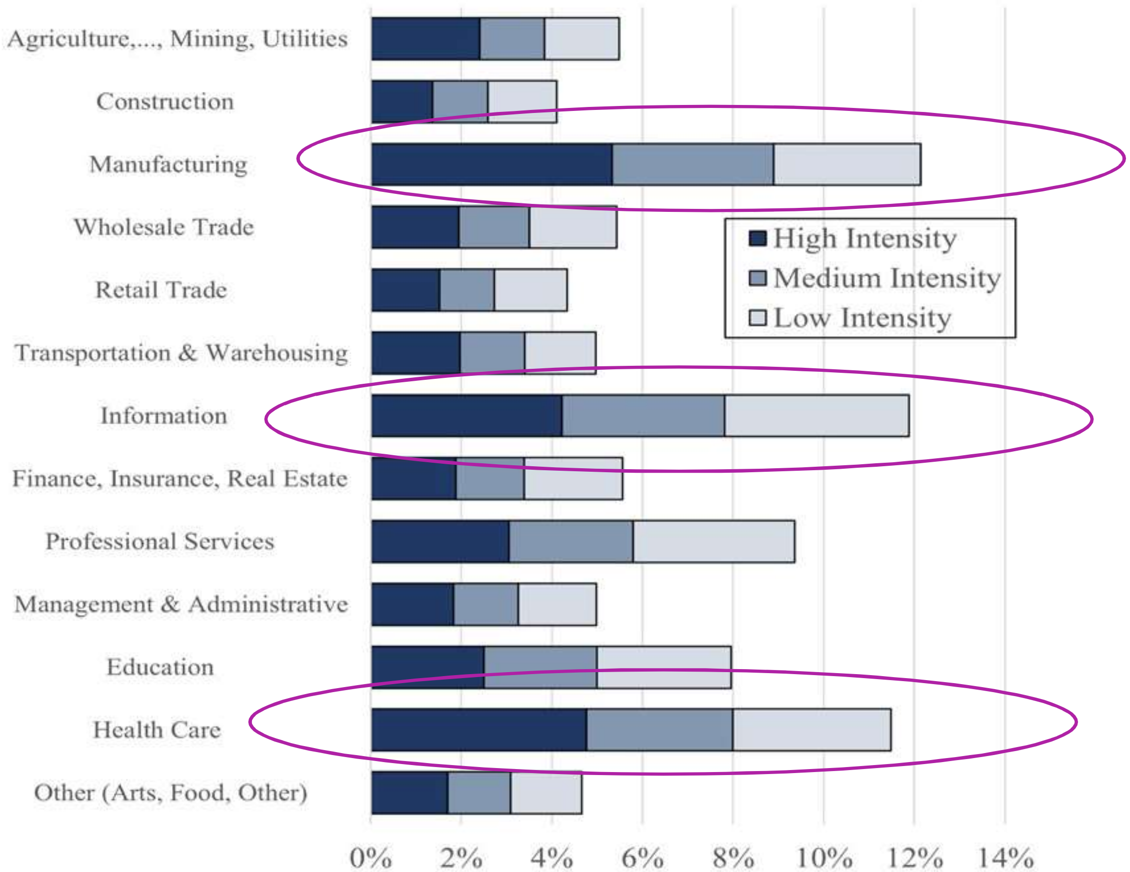
Skewness in AI Adoption



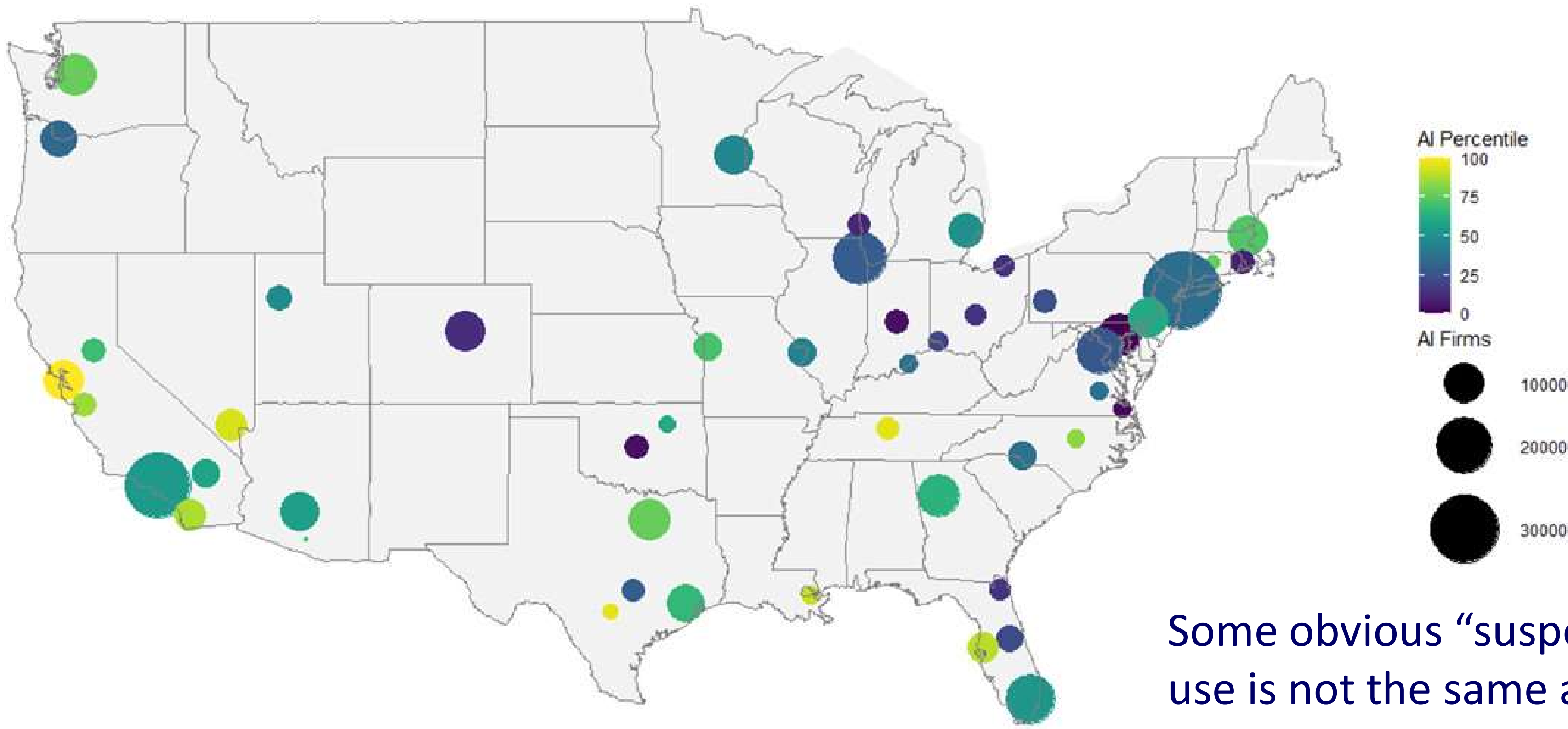
Average use of AI "in production" only 6%

62.5% among the largest firms (e.g., COMPUSTAT)

Heterogeneity abounds



Geographic Concentration of AI Use in Production



Some obvious "suspects" but use is not the same as invention, commercialization, or labor demand…

The Challenge of General-Purpose Technologies (GPTs)

- GPTs are pervasive technologies that **improve over time** and spark complementary innovation (Bresnahan and Trajtenberg 1995).
  - AI increasingly argued to be one (Trajtenberg 2018; Cockburn et al. 2018; Goldfarb et al. 2023, etc.)

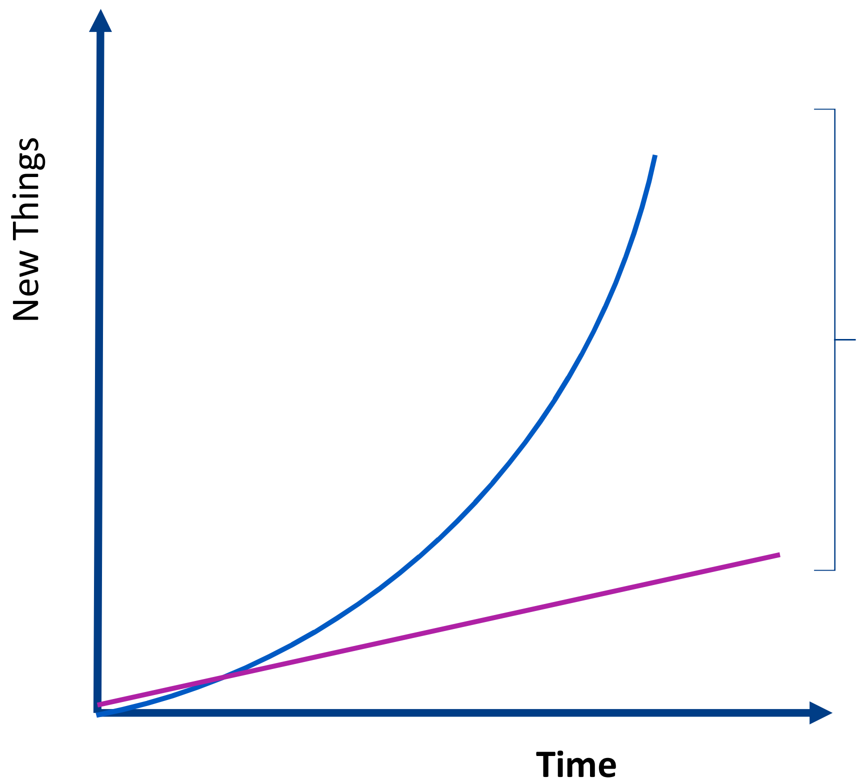
- Often require considerable **task, process, and organizational re-design** (David 1990; Bresnahan and Greenstein 1996; Bresnahan, Brynjolfsson, and Hitt, 2002; Feigenbaum and Gross 2024a&b)

- **System-level considerations** of value chains, markets, and ecosystems shape outcomes, too (Forman et al. 2012; McElheran 2015; Agrawal, Gans, and Goldfarb 2024; Bresnahan 2024; McElheran *any day now*…)

- Complementary adjustments require **inspiration, cash, and time**

- → **delayed and uneven effects,**
- → **increased impact over time**

Exponential Meets Linear Growth



How to close the gap?

1. Facts > Hype
2. **Attend to Co-Invention**
3. Weather the J-Curve

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The First SaaS Model

Age of Invention, by Anton Howes

Age of Invention: The First Intangibles Revolution

ANTON HOWES
MAR 31, 2023

45 17 7

How was it intangible? As Boulton and Watt put it themselves, "we only sell the licence for erecting our engines, and the purchaser of such licence erects his engine at his own expence." This was their standard response to potential customers asking how much they would charge for an engine with a piston cylinder of particular dimensions. The answer was, essentially, that they didn't actually sell physical steam engines at all, so there was no way of estimating a comparable figure. Instead, they sold licences to the improvements on a case-by-case basis — "we make an agreement for each engine distinctly" — by first working out how much fuel a standard, old-style Newcomen engine would require when put to use in that place and context, and then charging only a third of the *saving* in fuel that Watt's improvements would provide. "The sum therefore to be paid during the working of any engine is not to be determined by the diameter of the cylinder, but by the quantity of coals saved and by the price of coals at the place where the engine is erected." [1] They fitted the licensed engines with meters to see how many times they had been used, sending agents to read the meters and collect their royalties every month or year, depending on the location.

- Patent holders licensed the steam engine technology (rather than selling engines)
- Charged 1/3 of fuel savings
- Rise of rotary motion in factories posed challenges
- Changed to license fee based on horse power saved
- **Consulted extensively to support installations**

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Intangibles and the Productivity "J-Curve"

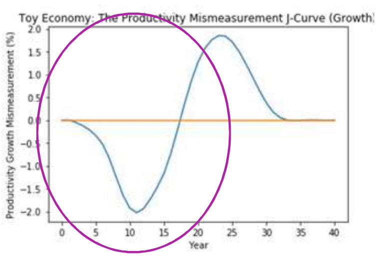
MIT INITIATIVE ON THE DIGITAL ECONOMY RESEARCH BRIEF 2019 Vol.2

THE PRODUCTIVITY J-CURVE:
HOW INTANGIBLES COMPLEMENT GENERAL PURPOSE TECHNOLOGIES

By Erik Brynjolfsson, Daniel Rock, Chad Syverson

On the margin, the (present-discounted and risk-adjusted) value of these unmeasured assets equals the costs incurred to produce them. But during the period in which that output is foregone, the firm's traditionally measured productivity will suffer because it will seem as though the company produces proportionately less. Later, when those hidden intangible investments start to generate a yield as inputs, a shift occurs and it will seem as though the measured capital stock and employed workers have spiked and become much more productive. Therefore, in early investment periods productivity is understated, whereas the opposite is true later when investment levels taper off.

The mismeasurement in this example regards a J-curve in productivity levels. That said, a similar J-curve exists for productivity growth rates. (See figure 1). Early in the GPT diffusion process, intangible investment growth is likely to be larger than intangible capital stock growth. With missed output growth dominating, measured TFP growth is lower than true TFP growth. Later in the GPT diffusion process, however, investment growth slows below the growth rate of the installed intangible stock. Eventually the growth rates equalize in steady state, and productivity mismeasurement disappears.



average $107 billion per year in 2017 dollars to explain the entire slowdown in in GDP growth. How much of this slowdown could be explained by a Productivity J-Curve for investment in AI and related intangibles?

The economy is early in the AI adoption cycle, yet the use of AI and robotics technology has rapidly increased since 2010 (Furman and Seamans 2018). Startup funding for AI has increased from $500 million in 2010 to $4.2 billion by 2016, growing by 40% between 2013 and 2016 (Himel and Seamans 2017). Though concentrated heavily in the IT sector, estimated total measurable corporate investment in AI in 2016 was $26 billion to $39 billion, marking 300% growth since 2013 (Bughin et al. 2017). Similarly, international industrial robot shipments since 2004 have nearly doubled overall and almost quadrupled in the consumer electronics industry (Furman and Seamans 2018).

For AI to account for the 0.55% of "lost" output in 2017 GDP, the quantity of correlated intangible investments per unit of tangible investment must be between roughly 2.7 to 4.1 times the observable investment values (using the Bughin et al. (2017) estimate).[3] This is not implausible. Research from 2002 found that the total market value of measured computer capital investments is as much as $11 per $1 in measured expenditure, with a standard error of $4.03.[4]

No such intangibles' "shadow" value will show up in the productivity statistics. The foregone output cannot be explained by growth in labor or observable capital inputs alone, so the output shortfall will be attributed to slower productivity growth. Further, this investment will later generate a capital service flow that produces measurable output.

Of course, these numbers are just for 2017, when measured AI investment was several times what it was only a few years prior. Thus, AI-associated intangibles are unlikely to explain most of the GDP growth slowdown. Looking forward however given that AI

- Investment in intangible complements and "co-invention" (Bresnahan and Greenstein 1996) are necessary for exploiting GPTs
- Difficult to measure
- Foregone output in the short term registers as a loss at the macro level
- Later, it is over-estimated and then balances out
- **Is there a way to pin this down at the micro level?**

THE RISE OF INDUSTRIAL AI IN AMERICA: MICROFOUNDATIONS OF THE PRODUCTIVITY J-CURVE(S)

BY

Kristina McElheran, MJ Yang, Zach Kroff, & Erik Brynjolfsson

https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5036270

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Disclaimer: Any opinions and conclusions expressed herein are those of the authors and do not represent the views of the U.S. Census Bureau. The Census Bureau has ensured appropriate access and use of confidential data and has reviewed these results for disclosure avoidance (DRB Approval Numbers for Project 7512395: CBDRB-FY24-CED006-0016, CBDRB-FY25-CED006-001).

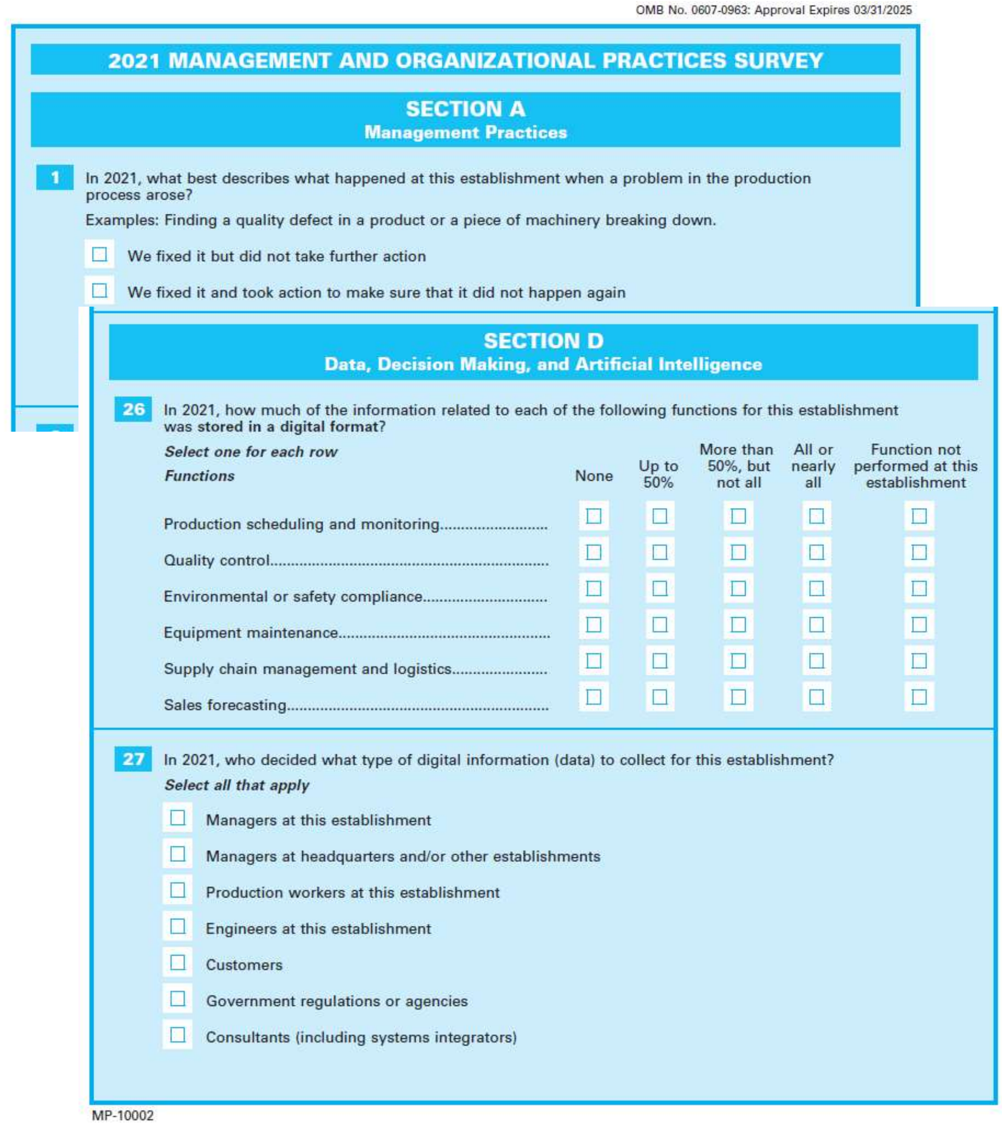
What We Do

- **Update** the Management and Organizational Practices Survey (MOPS) 2021 (Bloom et al. 2019, Brynjolfsson et al. 2021)
- **Link** to the 2018 Annual Business Survey & other U.S. Census Bureau data at the establishment and firm level
- **Disentangle**:
  - Org characteristics correlated with size
  - Other technology use
- **Triangulate on AI use**, which is actually a bundle of tools/applications (e.g., embedded in software, used across functions & specific applications)
- Learn about **barriers**
- Characterize:
  1. **Population-level diffusion in U.S. manufacturing as of 2021**
  2. **Correlates of AI use**
  3. **Impacts (OLS & IV) and dynamics (J-curve)**

MOPS 2021

1. U.S. Census Bureau estab-level survey
2. 3rd (updated) “wave”
3. 10% of all plants in US manufacturing sector; Certainty sample alone captures **70% of sector**
4. Response rate of **68%**

Average adoption rates are consistent with other population-weighted stats (McElheran ⓡ al. 2024; Bonney, et al. 2024)



OMB No. 0607-0963: Approval Expires 03/31/2025

2021 MANAGEMENT AND ORGANIZATIONAL PRACTICES SURVEY

SECTION A
Management Practices

1 In 2021, what best describes what happened at this establishment when a problem in the production process arose?

Examples: Finding a quality defect in a product or a piece of machinery breaking down.

☐ We fixed it but did not take further action
☐ We fixed it and took action to make sure that it did not happen again

SECTION D
Data, Decision Making, and Artificial Intelligence

26 In 2021, how much of the information related to each of the following functions for this establishment was stored in a digital format?

Select one for each row

Functions	None	Up to 50%	More than 50%, but not all	All or nearly all	Function not performed at this establishment
Production scheduling and monitoring	☐	☐	☐	☐	☐
Quality control	☐	☐	☐	☐	☐
Environmental or safety compliance	☐	☐	☐	☐	☐
Equipment maintenance	☐	☐	☐	☐	☐
Supply chain management and logistics	☐	☐	☐	☐	☐
Sales forecasting	☐	☐	☐	☐	☐

27 In 2021, who decided what type of digital information (data) to collect for this establishment?

Select all that apply

☐ Managers at this establishment
☐ Managers at headquarters and/or other establishments
☐ Production workers at this establishment
☐ Engineers at this establishment
☐ Customers
☐ Government regulations or agencies
☐ Consultants (including systems integrators)

MP-10002

Measuring AI Use

Artificial intelligence is a machine-based system that can perceive and learn about its environment and then make relevant predictions, recommendations, or decisions for an objective that is determined by humans.

- Extensively Tested
- 2 question blocks
  - By function
  - By specific technology/application
- Many applications!
- + Low adoption rates
- = No breakdowns disclosed for now…

In 2021, to what extent did this establishment **use artificial intelligence** (including machine learning algorithms in software applications) to support each of the following functions?

Select one for each row

Functions	None	Up to 50%	More than 50%, but not all	All or nearly all	Function not performed at this establishment
Production scheduling and monitoring	☐	☐	☐	☐	☐
Quality control	☐	☐	☐	☐	☐
Environmental or safety compliance	☐	☐	☐	☐	☐
Equipment maintenance	☐	☐	☐	☐	☐
Supply chain management and logistics	☐	☐	☐	☐	☐
Sales forecasting	☐	☐	☐	☐	☐

Select one for each row

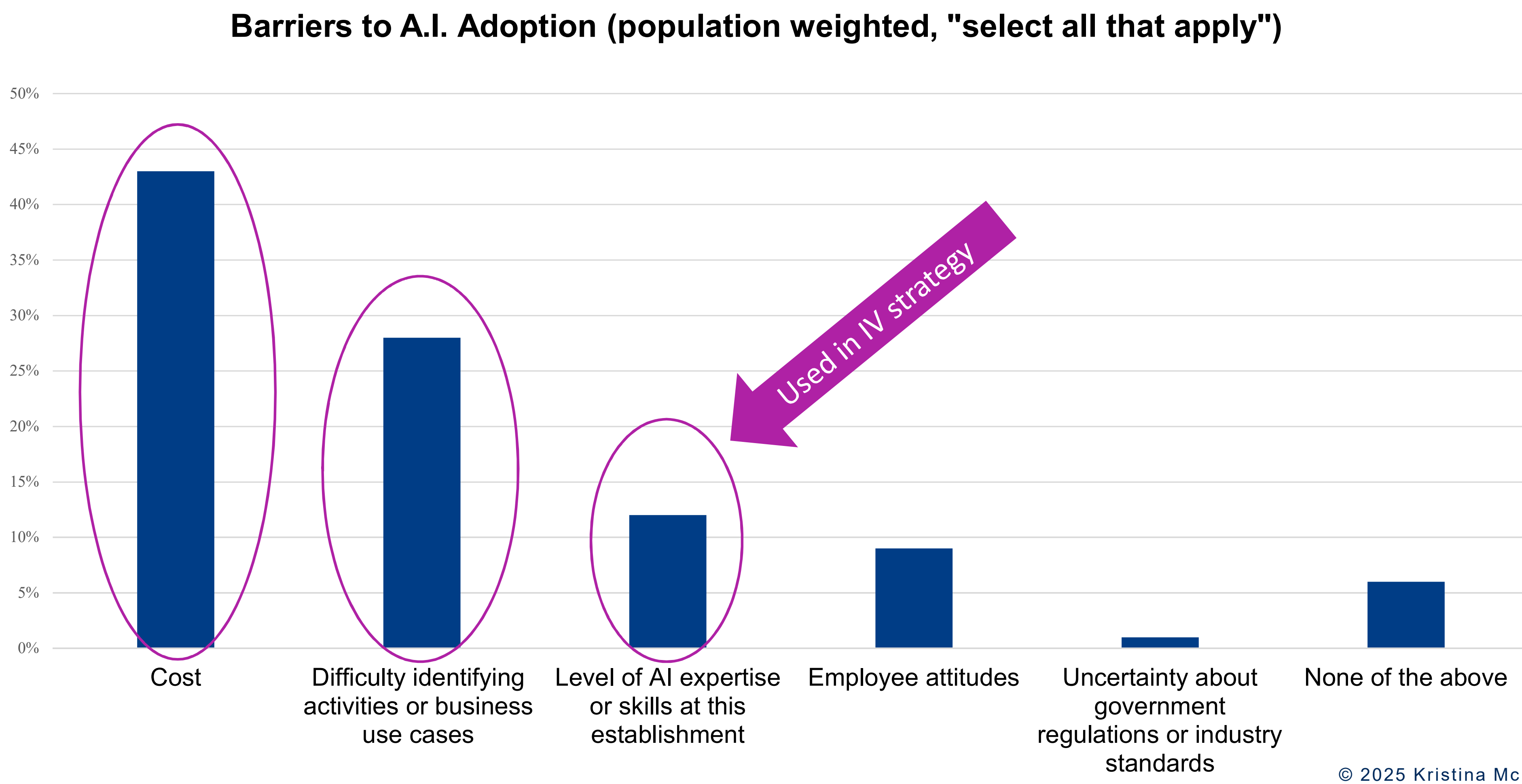
Applications	Did not use	Testing or piloting only	Up to 50% of direct production	More than 50% of direct production, but not all	All direct production	Don't know
Machine vision	☐	☐	☐	☐	☐	☐
Speech recognition	☐	☐	☐	☐	☐	☐
Predictive maintenance	☐	☐	☐	☐	☐	☐
Artificial intelligence-enabled industrial robots	☐	☐	☐	☐	☐	☐
Automated guided vehicles (AGV)	☐	☐	☐	☐	☐	☐

TOOLS ABOUND
Technology Use (population weighted)

Measure	Definition	Weighted Mean (C.V.)	Intensity (C.V.)
Digitization	At least some "**information stored in digital format**" (across six functions/activities)	**91%** (32%)	**64%** (52%)
Descriptive Statistics (DS)	Some use of "**descriptive analyses of data…typically used to support making key decisions**" (e.g., summary stats, time trends, dashboards, customized descriptive analyses)	**73%** (62%)	**52%** (77%)
Predictive Analytics (PA)	At least some use of "**statistical or algorithm-based models that analyze historical and current data to make predictions about future or unknown events…"** (across 6 business functions)	**65%** (74%)	**30%** (110%)
Any AI Application	At least some use of a "**machine-based system that can perceive and learn about its environment and then make relevant predictions, recommendations, or decisions for an objective that is determined by humans**"… OR at lest some use of one of the specific technologies (below)	**23%** (183%)	**8%** (250%)
Any specific technologies	At least some use of **machine vision, speech recognition, predictive maintenance, AI-enabled industrial robots, AGV**	**13%** (254%)	**2.3%** (391%)

N= ~30,000
*winsorized at 1st and 99th percentiles

Barriers to Adoption
U.S. Manufacturing, 2021 MOPS Survey



Estimating Performance

- **Performance**: Value-Added (output minus materials, etc.) & Profits

Controlling for:

- **Size (employment)**
- **IT K stocks** (capitalized investment 2019-2021)
- Other factor inputs: **K stocks**, energy (electricity and fuel)
- **Other organizational (establishment-level) features:**
  - Labor Skill (% bachelor's degrees)
  - Multi-Unit Status
  - HQ Status
  - Management Practices (non-data-related)
  - % Unionization
  - Production Design
- E-commerce intensity
- Value-Added Growth 2019-2021

SHORT-TERM Impacts of AI Use in U.S. Manufacturing

2021 MOPS

	(5)	(2)	(3)	(4)	(5)
DV	**Value-Added**	**Value-Added**	**Work-in-Progress**	**Log Robots**	**Log Employment**
Model	**OLS TFP**	**IV TFP**	**IV**	**Org Features**	**TFP**
AI Index	**-0.013**** (0.007)	**-0.587**** (0.230)	**2897**** (1408)	**0.412**** (0.184)	**-0.555**** (0.243)
Descriptive Analytics Index	0.015* (0.009)	-0.015 (0.017)	111.1 (103.2)	0.0390*** (0.0125)	0.0874*** (0.0166)
Predictive Analytics Index	-0.002 (0.007)	0.219** (0.089)	-1202** (545.8)	-0.155** (0.0710)	0.238** (0.0943)
Log ITK Stock	(+)***	(+)***	(+)**	(+)**	(+)***
Log Cloud Expense	(+)***	(+)***	(-)	(+)*	(+)***
Log Employment	(+)***	(+)***	(+)*	(+)***	
Log K stock	(+)***	(+)***			
3-Digit NAICS	Y	Y	Y	Y	Y
N ~30,000					

Change over Time & Heterogeneity (2017-2021)

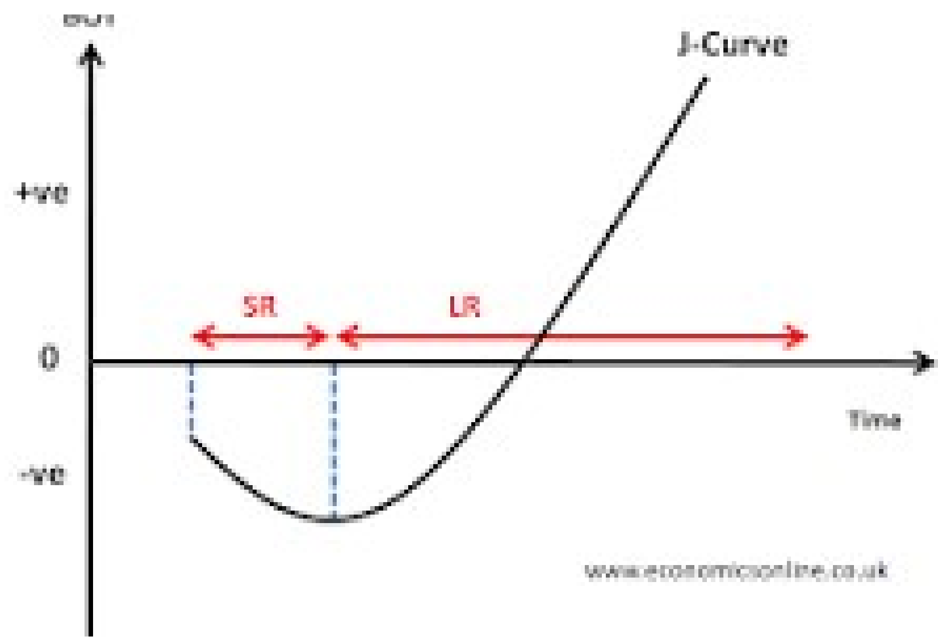
	Growth: Employment	Growth: Revenue	Growth: Labour Productivity	Growth: Revenue	Growth: Labour Productivity
AI Index	0.0084*** (0.0023)	0.0047*** (0.0018)	0.0034** (0.0016)	0.0330*** (0.0108)	0.0197** (0.0091)
AI Index x Log Age				-0.0090*** (0.0032)	-0.0051* (0.0227)
Controls for other technologies, size, production inputs (including K stock), employee skills, production design, unionization	Y	Y	Y	Y	Y
N=55,000 firms					

- AI use rises from 7.5% in 2017 to 9.1% in this sample
- Growth along multiple measures over time (including employment)
- Selects on survival
- Within-firm estimates will suffer more from attenuation due to measurement error

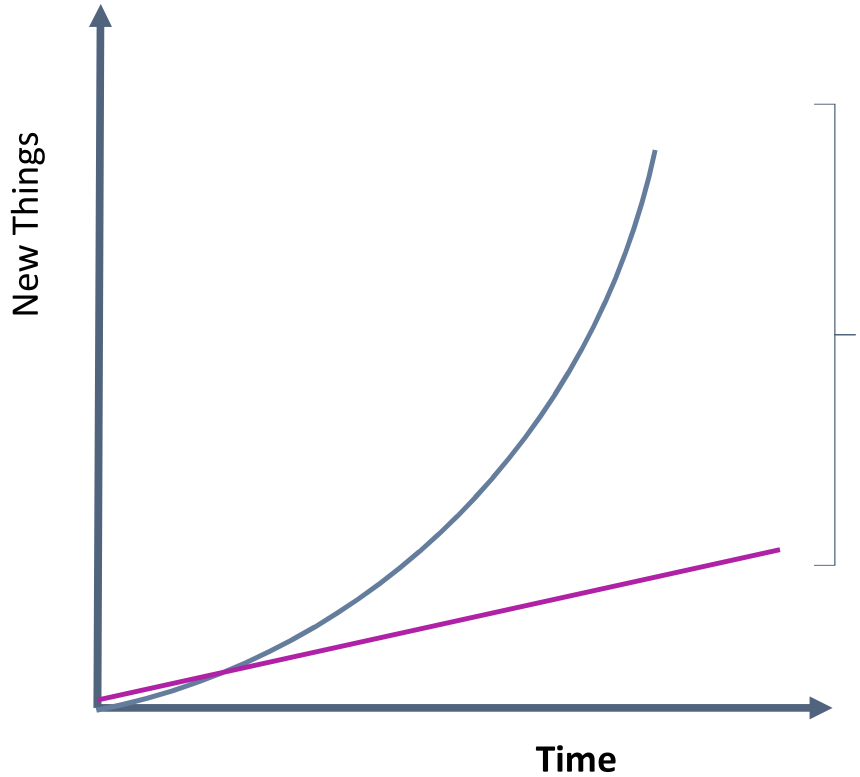
PUNCHLINE:

- Adoption is lower, on average, in representative sample, than many think
- The relationship between AI use and performance is
  - **<u>Negative</u> in the early, short term**
  - **Improves over time (2017-2021)**

- Sparks **organizational/process adjustment**
- Significant **heterogeneity** (diff't J-curve**s**)



This goes beyond measurement…



How to close the gap?

1. Facts > Hype
2. Attend to Co-Invention
3. **Weather the J-Curve**

More insights into **how** needed…

What happens to the humans?

- **"Automation vs. Augmentation" at the task level:**
  - Theoretically interesting, but "**exposure**" is doing a lot of the work
  - Often fixed in models, but <u>not fixed in life</u>:
    - **Task content** of work
    - **Allocation** of time within jobs
    - **Value** of diverse tasks
    - **Cost** structure of tasks
  - **Interdependencies** across tasks will matter
  - Automation can **improve** many aspects of work (i.e., it's not just a "trap" or a design problem)

DALL-E October 2024

- **Use recent history as a guide?**

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Journal of Econometrics
Volume 233, Issue 2, April 2023, Pages 443-467

Twisting the demand curve: Digitalization and the older workforce

Erling Barth [a] [b], James C. Davis [c], Richard B. Freeman [b], Kristina McElheran [d]

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Abstract

CONCLUSIONS

1. **Not all firms should be considered "at risk"** of using AI-related technologies, despite their general-purpose nature
2. Ongoing (representative) **measurement is essential**
3. Evidence points to **short-term pain for longer-term gain**
   - Pain is nontrivial
   - Adjustment costs are distributed unevenly (**varied J-curves**)
   - More sector-specific insights needed
4. **Worker concerns** have merit
   - Short-term labour shedding
   - Rising physical automation
   - Skill- and age-biased technologies require more research and policy attention

Thank you!

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