How It's Made: A General Theory of the Labor Implications of Technological Change

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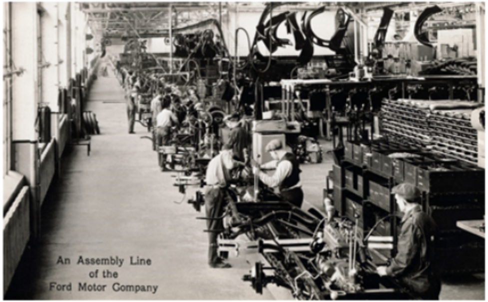
Technological Change Transforms Labor

20th Century Assembly Line | 21st Century Assembly Line



Source: Ford Motor Company

Source: Getty Images

Not All Technological Change is Equal

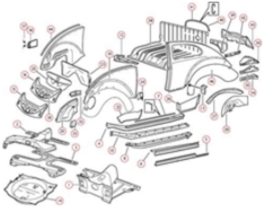
20th Century Assembly Line

Source: Ford Motor Company

21st Century Assembly Line

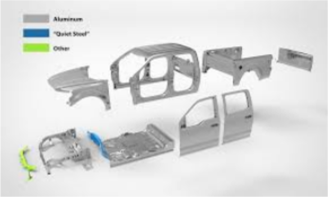
Source: Getty Images

20th Century Auto Body



Source: Volkswagen

21st Century Auto Body



Source: SAE international

No Unified Theory To Explain Skill Demand Effects

- **Skill-biased technological change**: Largely, technological change driving demand from low to high skill (e.g. Katz and Murphy 1992, Graetz and Michaels 2018); polarizing from mid-skill (e.g. Autor and Dorn 2013, Goos, Manning and Salomons 2014)

- And yet, examples of SBTC varying with time (Card and Dinardo 2002), context (Brynjolfsson, Mitchell and Rock 2018), and technology (Goldin and Katz 1997)

Unanswered Questions

- **Why** do technologies **differ** in their effects?
- **What** are the **origins** of the effect of skill demand on technology?

A General Theory to Answer Both Questions

- Problem of the firm: dividing and assigning production tasks
- Five dimensions that technology can affect
  1. Overall complexity of process
  2. Cost of dividing tasks into steps with different performers
  3. Sensitivity of performers to the rate of production
  4. Sensitivity of performers to the number of tasks in a step
  5. Cost of dividing performers among multiple steps
- Recover how the demand for workers' skill level is endogenously determined

A Model Built on the Shoulders of Giants

- Opposing, multimodal effects of technological change on skill demand
  (Goldin and Katz 1998, Autor and Dorn 2013)

- Machine and step-level data to recover production function
  (Kurtz and Manne 1963, Enos and Pearl 1975)

- Assignment of heterogeneous workers (and machines) to different tasks
  (Rosen 1978, Lindelaub 2016, Acemoglu and Restrepo 2019, Haanwinckel 2020)

This paper builds on task assignment and process models

- Endogenizes job assignment, but also the complexity of jobs.
- Provides engineering microfoundations of task-performer complementarity.

To Support a General Theory: Broad and Deep Data

	Dataset	Key Variables	Sectors	Data Size
Historical	**Hand and Machine Labor** (Wright 1898)	Wages, Process Flow, Performer Type, Operational Inputs	Manufacturing, Agriculture, Mining, Transportation	15,700 Steps 247,000 Variables
Contemporary	**Optoelectronic Semiconductors** (Combemale, Whitefoot, Ales, Fuchs 2021)	Skills, Process Flow, Performer Type, Operational Inputs	Manufacturing	481 Steps 11,000 Variables

Additional Data: Contemporary Automobile Assembly (Fuchs, Roth and Kirchain 2008)

Problem of the Firm: Minimize Production Cost

Firm makes product of given volume for least cost by:

- Breaking tasks into steps
- Assigning performers (human, machine)
- Determining the rate of production (and thus ability demand)

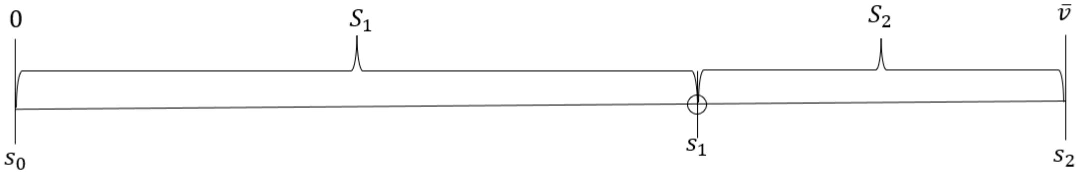
$$\overset{\text{Cost}}{\overset{\downarrow}{C}}(\underset{\underset{\text{Volume}}{\uparrow}}{R}, \overset{\text{Number of Steps}}{\overset{\downarrow}{T}}) = \min_{\{s_i\}_{i=1}^{T}, \{r_i, a_i, o_i\}_{i=1}^{T}} \sum_{i=1}^{T} \underset{\underset{\text{Performer Cost}}{\uparrow}}{p}(\overset{\text{Ability}}{\overset{\downarrow}{a_i}}, \underset{\underset{\text{Rate}}{\uparrow}}{r_i}, R | \overset{\text{Performer Type}}{\overset{\downarrow}{o_i}}) + \sum_{i=1}^{T} \underset{\underset{\text{Fragmentation Cost}}{\uparrow}}{f}(\overset{\text{Task}}{\overset{\downarrow}{s_i}}, o_i)$$

- Firm chooses how much to divide by optimizing over number of steps T

$$C(R) = \min_{T \in \mathbb{N}_+} C(R, T)$$

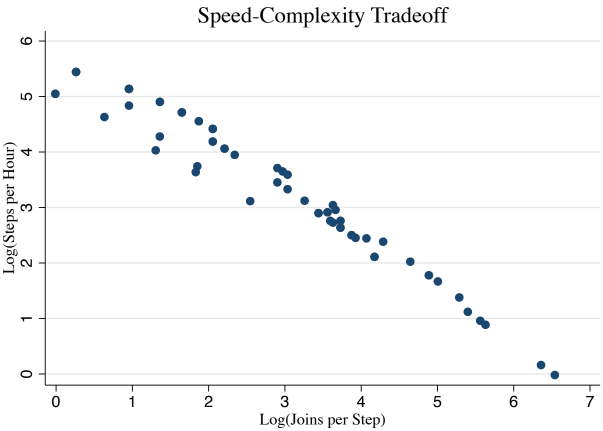
Firms Break Tasks into Steps

- To make a product, an **interval of tasks** must be completed: $\mathcal{V} = [0, \bar{v}] \subset \mathbb{R}_+$
- **Firms break tasks into steps** (S_i), defined by a series of T thresholds
  - Firms assign a performer (o_i) to each step: human (h) or machine (m)
  - **Length** $l_i = s_i - s_{i-1}$ tasks contained in a step, stochastic issues arrive rate λ
- **Key Ingredient**: Dividing tasks has **fragmentation cost** $f(s_i, o_i)$



Origins of Ability Demand: Complexity and Rate

Difficulty of a step $D(c, r|o)$ increases in complexity, rate (chosen by firm)

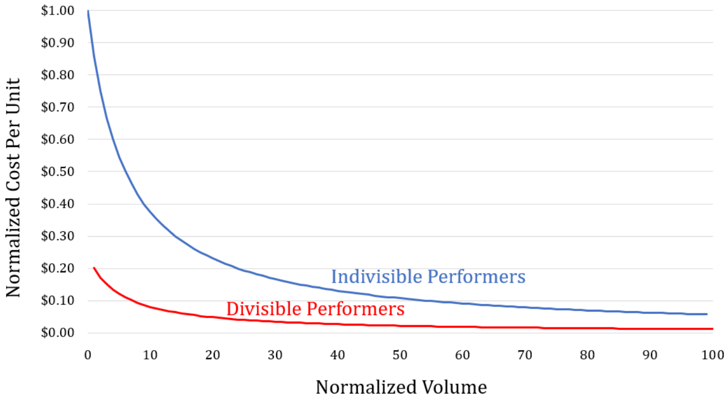


Data: Fuchs, Field, Roth, Kirchain (2008)

- Humans have higher **generality** (ρ) than machines at solving issues:
  Complexity $c(l|\rho)$ increases in length, more for machines than humans
- **Sensitivity of difficulty to rate** is higher for humans than machines
- Performers have **ability** a: if $a < D$, then completion of step fails.

Returns to Higher Rate Constrained by Divisibility

Number of performers demanded depends on volume, rate: $g(R, r)$

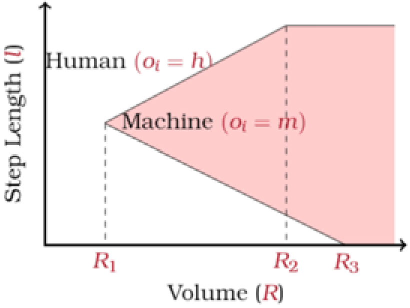


Data: Combemale, Whitefoot, Ales and Fuchs (2021)

- Reallocation cost imposes upper bound economical rate, $\bar{r}_i(R)$
- More volume means less idle time: $\bar{r}_i(R)$ increasing in
- Humans more divisible than machines (lower reallocation cost): For all R, $\bar{r}_h(R) \geq \bar{r}_m(R)$

Which Steps Are Automated? Historical Case

Mechanization of process steps (1880s-1890s)



Theory: Cone of Automation
(Propositions 3-7)

Relative Wage (Step Length)

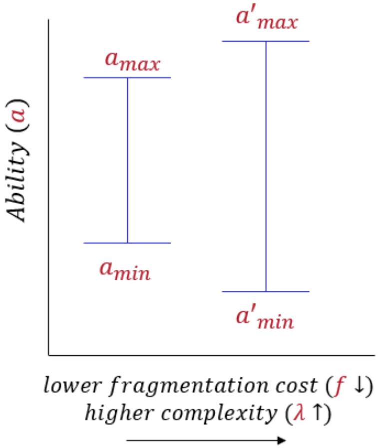
17%	29%	17%	25%	30%	33%	44%	40%
25%	21%	35%	14%	47%	58%	63%	74%
25%	52%	50%	40%	52%	48%	58%	93%
17%	Insuff. Data	30%	57%	63%	40%	78%	91%
35%	60%	56%	70%	62%	68%	76%	91%
38%	53%	59%	44%	67%	68%	91%	91%
39%	42%	40%	35%	72%	71%	76%	77%
30%	41%	40%	41%	29%	65%	65%	64%

Performer Utilization (Maximum Productive Rate)

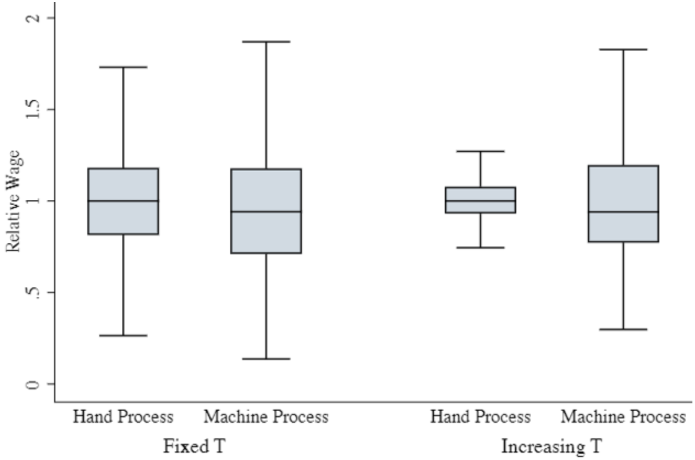
Empirics: Rate of Automation

Which Tasks are (Dis)Integrated? Historical Case

Rise of professional managers, adoption of interchangeable parts (1880s-1890s)



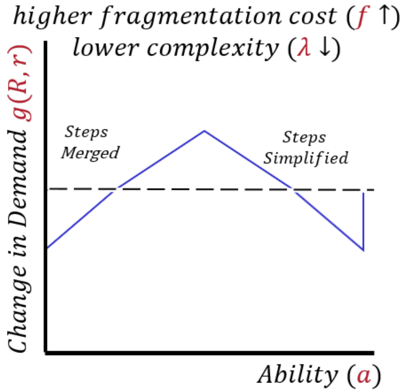
Theory: Distribution of Ability
(Lemma 3; Corollaries 1 and 2)



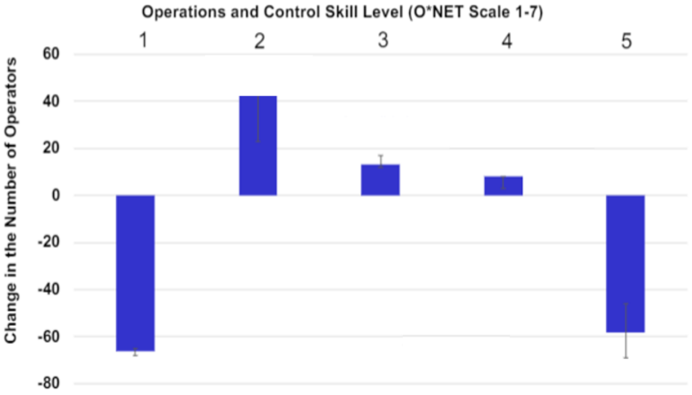
Empirics: Distribution of Wages

Which Tasks are Integrated? Contemporary Case

Integration of parts and streamlining of process design (2000s-2010s)



Theory: Changing Ability Demand
(Lemma 3; Corollaries 1 and 2)



Empirics: Changing Ability Demand

Conclusion

- **Technology affects skill demand on three dimensions of problem of firm**
  - Ease of fragmenting production tasks
  - Cost of allocating performers to multiple different steps
  - Trade-off between step complexity and rate of completion
- Theory explains why some technologies polarize skill, some drive convergence
- Theory explains how skill demand effects of technology vary with context