Discussion of "Capability, Technological Change and the Wage Distribution"

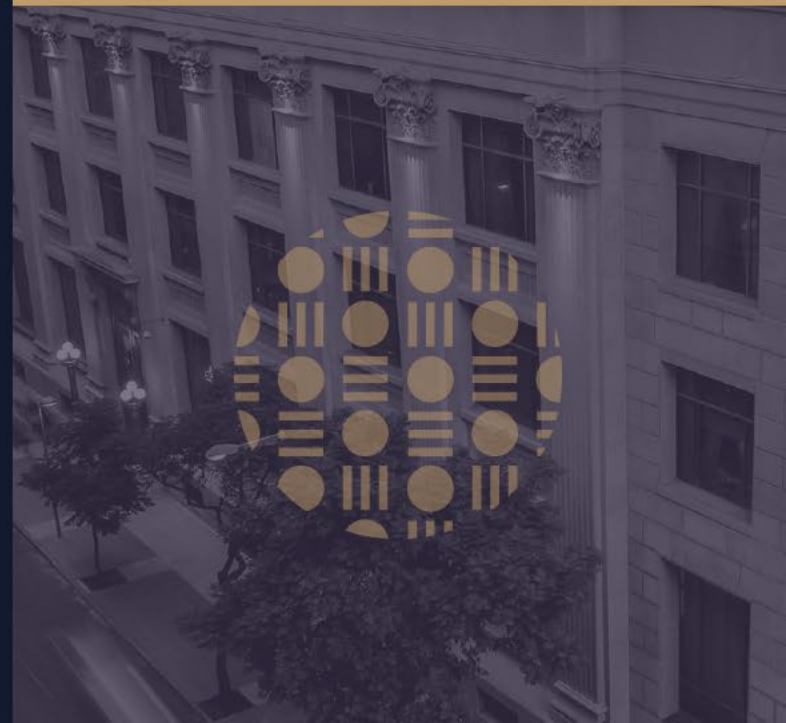
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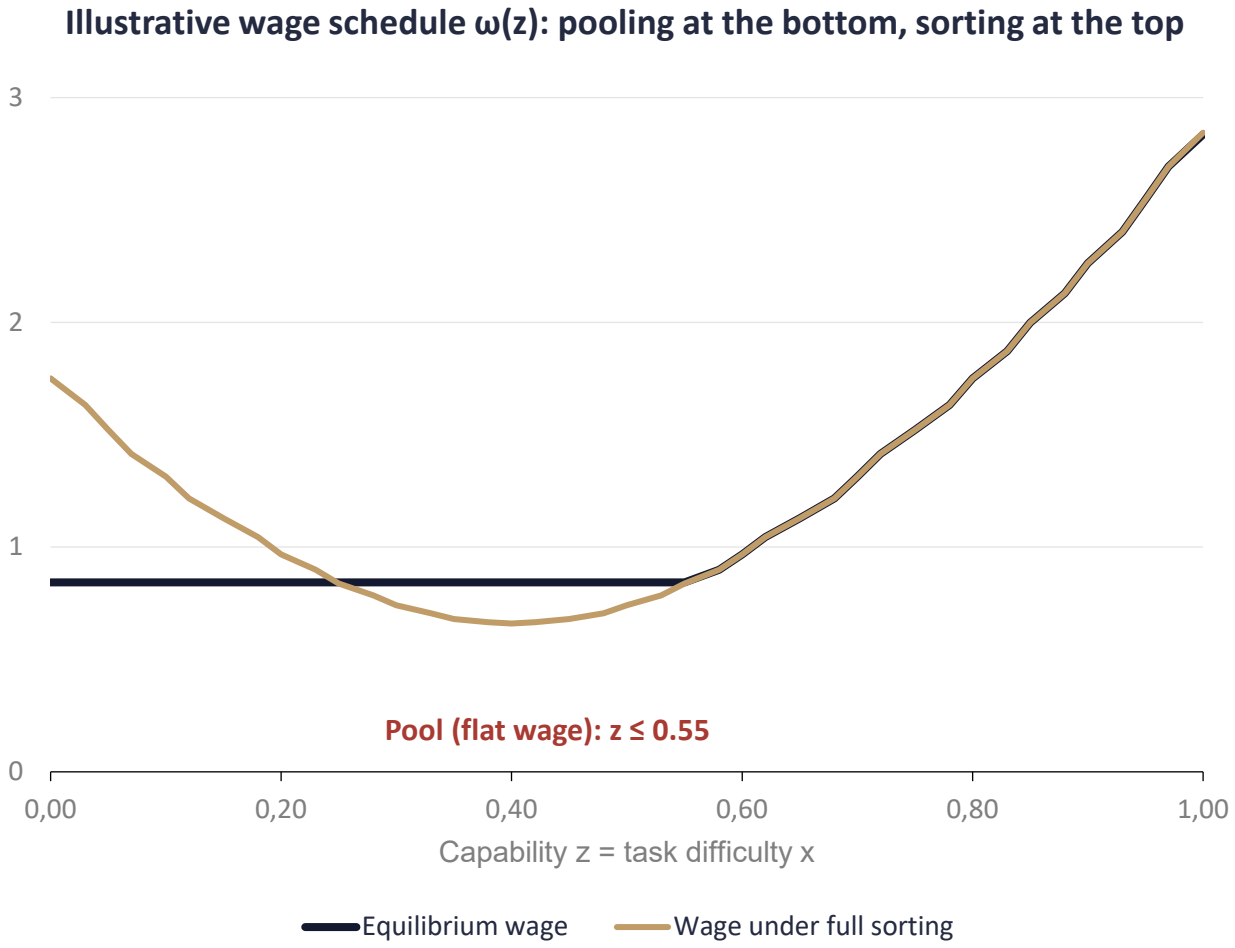
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Summary: a task-based model of the wage distribution

Workers differ in which tasks they can perform, and production combines many tasks. Depending on relative supply-demand for tasks, flat-wage regions with overqualified workers can arise.



- **Technology:** worker z can do tasks x ≤ z; all capable workers are equally productive. Tasks are combined with CES function and have productivity g(x) (task "weight").
- **Wages belong to tasks, not to abilities:** ω(x) = Y^(1/σ)·[g(x)/m(x)]^(1/σ); a worker earns the best ω(x) with x ≤ z.
- **Sorting fails where f/g rises:** harder tasks would be relatively crowded and pay less. Capable workers step down, wages flatten, some are overqualified.
- **Solution:** least concave majorant of F against G ("ironing"). Pool locations depend on relative tasks-weights distribution; equilibrium is efficient.

Note: chart is an illustration computed for this discussion, with g(x) = 1, σ = 2 and a truncated Student t capability distribution (2 d.f., location 0.40, scale 0.173), as in the paper's Fig. 2 but without the top winsorization. Source: Kaplan and Mahadevan (2026), Section 2.

Overall: a useful model for a technological change we do not yet understand

Equilibria can differ widely, even qualitatively, depending on calibration and what the AI shock means. The model is flexible enough to accommodate different interpretations of the AI shock.

1. What is the AI shock? The paper's three (static) experiments

New tasks?
Exp. 1: difficult tasks only the most capable can do
Top-pool workers gain. Effects on others depends on σ (*intuition?)*

A tool that upskills (low ability) workers?
Exp. 2: low-capability workers can do harder tasks
New middle pool; bottom-workers gain, workers just above lose.
Parameter dependent.

Difficulty-biased technical change?
Exp. 3: harder tasks become relative more productive
Gains concentrated at the top. *Effect on other workers depends on σ.*

2. Dynamic extension: workers invest in capability

Investing implies endogenous future capabilities, with convex cost to investment. Rational, equilibrium wages thus inherit convex shape (my intuition at least).

Source: Kaplan and Mahadevan (2026), Sections 3.1-3.3 and 4.3.

The model can accommodate several technological changes; ability and productivity distributions; substitution parameters, etc. *Where to go next?*

1 **Relation to the literature**

2 **Model features**

3 **Interpretation of AI**

Comment 1: relation to the literature

Deeper discussion about relation with reference papers: i) automation and displacement effect of capital, ii) automation and expertise, iii) empirical wage distributions and underlying mechanisms.

	Acemoglu & Restrepo (2022); AKR (2025)	Autor & Thompson (2025)	Kaplan & Mahadevan
Mechanism	Automation displaces labor from tasks	Automation changes the expertise a job requires	AI Shifts capability supply and task weights
Capital	Displaces workers (receives "wages" of affected occupations)	Takes over certain tasks within occupations	Absent: technology only redistributes among workers
Wages	Fall for groups displaced from routine tasks	Depends on which tasks are displaced. Negative correlation between wages and employment.	Scarcity; flat within pools. How do "experiments" relate to automation findings?
Employment	Falls where tasks are lost	Opposite to wages: more workers qualify when expertise falls	Not a margin (full employment)
Evidence	50–70% of US wage-structure changes, 1980–2016	Four decades of task removal and addition, 303 occupations	None yet

Autor & Thomson: Clerks, 1980–2018

Accounting: jobs 1.62m → 1.11m; log wage 2.57 → 2.90

Inventory: jobs 0.54m → 1.48m; log wage 2.66 → 2.52

Links to explore. (i) How would the model, or an experiment, capture displacement by capital? (ii) AI raising the capability of low-z workers (Exp. 2): is it similar to Autor–Thompson's "automating expert tasks"?. Does it lead to opposite conclusions? (upskilled workers see higher wages).

Sources: Acemoglu and Restrepo (2022), Econometrica 90(5); Acemoglu, Kong and Restrepo (2025), Handbook of Labor Economics vol. 6; Autor and Thompson (2025), NBER WP 33941 (clerk figures from footnote 5).

Comment 1 (cont.): what do wage distributions say?

Use the empirical wage distribution to discipline the model. In the literature, pooling at the bottom exists, but due to other channels.

Paper	What it shows	What it attributes it to
Cengiz, Dube, Lindner & Zipperer (2019)	Jobs bunch at and just above a new minimum wage; modest spillovers above; no net loss of low-wage jobs (138 US state increases)	**Wage floor (policy)**
Autor, Dube & McGrew (2023)	Post-pandemic compression: fast wage growth at the bottom reversed about one third of the 40-year rise in the 90/10 gap	**Tight labor markets, weaker employer power: workers climbing job ladders**
Leuven & Oosterbeek (2011)	Overqualification is common, but surplus schooling still earns a positive (smaller) return	**Mismatch: compression, not a flat wage**

Can features of observed wage distributions pin down f, g and σ? And which prediction of capability pooling can minimum wages and monopsony not produce?

Sources: Cengiz, Dube, Lindner and Zipperer (2019), QJE 134(3); Autor, Dube and McGrew (2023), NBER WP 31010; Leuven and Oosterbeek (2011), Handbook of the Economics of Education vol. 4.

Comment 2: the model

Which findings are general (e.g., propositions), and how do they translate into testable predictions? Which are doable and important extensions?.

a) Propositions vs. calibration

Exp. 1, share of workers with higher wages:

100%	7.2%	0%
σ = 2	**σ = 1**	**σ = 0.5**
output +8.0%	output −14.1%	output −43.3%

- **More general:** pools share shocks; separation boundaries block spillovers; pool locations and relative wages do not depend on σ.
- **Parameter-dependent:** level effects, who gains, where pools form.

b) Disutility from "effort"

Overqualified workers are indifferent from working in higher ability tasks that pay the same wage. If effort is costly, pooling may disappear (intuition from dynamic investing in capabilities).

c) Tasks vs. jobs

Occupations are collections of tasks. Does the separation–pooling logic carry through, approximately (a low slope rather than flat), when jobs are composites of tasks?

d) Link with capital

It is hard to think of AI, tasks and wages without the displacement effect: AI as capital displacing labor in some tasks, and perhaps entire occupations.

Source: Kaplan and Mahadevan (2026), Table 1 and Sections 2-3.

Comment 3: what is AI about? How does “getting IA wrong” matter for young people?

Three exercises, all interesting. How can we give them more discipline to get sharper insights? How does “Getting it wrong” matter for ***dynamic skill investment***?

a) Which one?
Which of the three experiments is AI most likely to be: new tasks, an upskilling tool, or difficulty-biased productivity?

b) Are there more possibilities?
In Autor–Thompson, technology removes tasks. Add an experiment that removes tasks at the bottom or middle of the difficulty ladder, to compare with displacement in the task literature.

c) The investment exercise matters most for policy

- In the model, investing in ability leads to wage separation. Investments are rational and optimal.
- But there is huge uncertainty about how IA will disrupt work (e.g., 3 experiments)!
- If young people make the wrong, irreversible career investments, there might be a lot of pooling into a crowded region: disappointment and social discontent.
- Suggested experiment: explore aggregate-level shock that induces ex-post pooling. Would this lead to underinvestment today?

Sources: Kaplan and Mahadevan (2026), Sections 3.1-3.3 and 4; Autor and Thompson (2025), NBER WP 33941.

Fun, flexible model with many possible future directions!

Thanks!