ECON2840 Spring 2024
Paper Presentation

Daron Acemoglu, The simple macroeconomics of AI, Economic Policy, Volume 40, Issue 121, January 2025, Pages 13–58

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March 10, 2025

Context and Motivation

A lot of hype, hindisght from robotization, first experimental results

- In the media:
  - Science fiction fantasies,
  - ChatGPT: fastest spreading tech mlatform in history,
- In the business world:
  - Goldman Sachs (2023): Over ten years, 7% increase in global GDP, 1.5% annual increase in US productivity growth,
  - McKinsey Global Institute (2023): a USD 17-26 trillion increase to the global economy.
  - 12% of the labor force.
- Recall robotization (Acemoglu, Restrepo, 2020):
  - Positive outcomes on firm owners and managers,
  - Negative outcomes on workers.
- Experiments: nontrivial productivity gains driven by improvements for less productive/lower-performing workers.

Research question and strategy

What insight can we get, from the Macro labor toolbox, on the outcomes of AI for a ten-year horizon?

- Fitting the Task.Skill.Capital framework from Acemoglu, Autor (2011); Restrepo (2018, 2019, 2022),
- Empirical calibration and prediction.

Model

Production

- A unique final good,
- All markets are competitive,
- A continuum of tasks: $[0; N]$,
- Output of task z: $y(z)$,
- Production function: $Y = B(N)\left(\int_0^N y(z)^{\frac{\sigma-1}{\sigma}} dz\right)^{\frac{\sigma}{\sigma-1}}$,
- Constant elasticity of substitution (tasks are complements): σ,
- System-wide effect of new tasks: $B(N)$,
- Task production function: $y(z) = A_L \gamma_L(z) l(z) + A_K \gamma_K k(z)$ (in fact $y(z) = A_L \gamma_L(z)[l(z)^{1-\kappa} k_C(z)^{\kappa})] + A_K \gamma_K k(z)$),
- labor/capital-augmenting productivity terms: A_L, A_K,
- Labor/capital task-specific productivity schedules: $\gamma_L(z)$, $\gamma_K(z)$.

Assume $\frac{\gamma_L(z)}{\gamma_K(z)}$ increasing in z.
Hence labor has a comparative advantage in higher-indexed tasks.
Hence $z \in [0; I]$ is produced via capital; $z \in]I; N]$ is produced via labor.

Labor, capital, consumption

- Measure-one population,
- High and low skill labor for fractions Φ^H, Φ^U of the population endowed with λ^H, λ^U units of labor (tasks can be performed by either),
- $\lambda^U < \lambda^H$,
- Supply of labor: $\Phi^H \lambda^H + \Phi^U \lambda^U = \mathrm{L}$,
- Wage rate: ω,
- Aggregated capital: $K = \int_0^N k(z)dz$
- Task-specialised capital $k(z)$ produced linearily from final good Y with price $R(z) = R(K)\rho(z)$,
- Households consume the final good net of capital expenditures.

Equilibrium

Characterization of an equilibrium:

- z is produced by labor iff:

$$\frac{\omega}{A_L\gamma_L(z)} < \frac{R(z)}{A_K\gamma_K(z)}$$

,

- $$k(z) = argmax_{k(z)}\{Y - R(z)k(z)\}$$

,

- Labor market clearing:

$$L = \int_0^N l(z)dz$$

.

We skip the solution. The point is to compute comparative statics.

Towards comparative statics: how AI affects production

- Extensive margin automation i.e., increase in I:
  - AI reduces the cost of capital $\rho(z)$ for some marginal tasks above I,
  - AI increases the effectiveness of capital $\gamma_K(z)$ for some marginal tasks above I,
- Greater task complementarities, for $z \in [0; I]$:
  - AI raises the task-specific productivity of labor $\gamma_L(z)$,
  - AI reduces the cost of complementary capital $k_C(z)$,
- Intensive margin automation, for $z \in [0; I]$:
  - AI reduces the cost of capital $\rho(z)$,
  - AI increases the effectiveness of capital $\gamma_K(z)$,
- New labor-intensive products or tasks i.e., increase in N:
  - "Good" or "bad" in terms of social value, possibly causing externalities.

Comparative statics

- Ambiguous sign of $\frac{dln\omega}{dI}$:
  - Increase in productivity $\rightarrow$ Increase in wages,
  - Displacement of workers across tasks $\rightarrow$ Decrease in wages.
- Ambiguous sign of $\frac{dln\omega}{d\gamma_L(z)}$:
  - Increase in easiness to perform $\rightarrow$ Decrease in task price not fully offset,
  - Unclear offset by increase in productivity.
- For $z \in [0; I]$, $\frac{dln\omega}{d\gamma_K(z)} > 0$, $\frac{dln\omega}{d\rho(z)} > 0$, $\frac{dN}{d\rho(z)} > 0$.

Simplifying the job for aggregates: Hulten's theorem

How micro-level productivity improvements translate into macro changes.

$$GDP = Y = \int_0^N p(z)y(z)dz$$

At the equilibrium, any small change in an element of $\{B; A_L; A_K; \gamma_L(z); \gamma_L(z); I; N\}$ (technology) has second-order impact on GDP via:

- Reallocation of factors across tasks,
- Prices.

This takes us to

$$dlnY = dlnTFP + S_K dlnK$$

(with s_K the capital share of GDP) and

$dlnTFP =$ Costs savings from automation$*$GDP share of AI-impacted tasks

Finalizing the theory

- Distinguishing between easy and hard to learn tasks
  $\rightarrow$ Different productivity gain magnitudes,
- Welfare analysis including the negative exterality from "bad" tasks,
- Inclusion of multiple demographic groups
  $\rightarrow$ Theoretical arguments in favour of rising inequality due to an increase in the productivity of low-skilled workers.

Empirics

Logic, sources, first estimates

Estimates of which tasks can be automated with AI; Estimates of the cost savings; Estimates of new tasks.

$\rightarrow$

TFP growth estimates; GDP growth estimates; Wage growth estimates; Inequality implications.

- GDP share of tasks impacted by AI within the next 10 years:
  - Eloundou et al. (2023) $\rightarrow$ Ask GPT-4 to classify O*NET 19,265 tasks and 2,087 Detailed Work Activity and infer an automation index.
  - U.S. Bureau of Labor Statistics National Occupational Employment and Wage Estimates.

  4.6%.
- Cost savings from AI:
  - Peng et al. (2023),
  - Noy and Zhang (2023),
  - Brynjolfsson et al. (2023).

  20.5%.

TFP growth, GDP growth, bad tasks

- TFP growth over 10 years:
  - Ignoring hard and easy tasks:
    0.71%. Likely to reach 1% if the cost of AI decreases optimisticly over time,
  - Considering hard and easy tasks:
    0.55%. Likely to reach 1% if the cost of AI decreases optimisticly over time,
- GDP growth over 10 years:
  - Ignoring hard and easy tasks:
    1.1%,
  - Considering hard and easy tasks:
    0.92%,
- Bursztyn et al. (2023) (estimate the welfare effect of social media): Currently 0.072% of GDP, sizable effect on welfare.

Wages and inequality

Acemoglu and Restrepo (2022): The chore of the reasoning is the ripple effects: the displacement of one demographic group impacts others.

- Least exposed: workers with less than high school,
- Medium: postgraduate workers,
- Most exposed: workers with college degrees and those with high school degrees or some college.

Within the next ten years:

- Predicted wage impacts do not appear to increase inequality between education groups.
- Predicted impact on GDP considering hard and easy tasks: 1.62%.
- Predicted impact on capital share considering hard and easy tasks: 0.38%.

Consequences on inequality of AI will not be as adverse as those from pre-AI automation.
No evidence of inequality reduction.

Conclusion