Innovation, Automation, and Inequality: Policy Challenges in the Race against the Machine

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Motivation

Common assumption in growth economics:

- technological progress is labor-augmenting,
- it makes workers more productive.

However, there is a dark side of technological progress:

- only some workers become more productive,
- others might become redundant.
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Figure 1: Worldwide Stock of Operational Industrial Robots (source: IFR, 2018)
Standard R&D-based growth theory: More innovation leads to

1. higher GDP and higher overall labor income.

However:

2. higher income of skilled labor; stagnating income of low-skilled labor;
   ⇒ increasing skill premium, wage polarization, rising income inequality,

3. declining labor income share,

4. rising wealth inequality,

5. increasing educational attainment.

Our aim:

Building an R&D-based growth model with automation that explains 1-5.

Crucial differences in assumptions:

- New goods/tasks are non-automated. Firms make effort to automate these tasks/goods in a later step.
- No education.
- No redistribution.

⇒ They support more benign conclusions.

But:

Empirical study by Acemoglu and Restrepo (2017) acknowledges that their earlier view might have been too optimistic.
Assumptions

OLG economy: individuals live for 3 periods.

- Youth: basic education
- Working age and decision on high-skill upgrade (college)
- Retirement

3 production factors:

- l-types: low-skilled, substitutes to machines, routine tasks, easy to automate, work in goods production (assembly line workers),
- h-types: high-skilled, complements to machines, difficult to automate (engineers and scientists),
- Physical capital in the form of machines/robots.
Utility function:

\[ u_t = \log(c_{j,t}) + \beta \log(\bar{R}_{s_j,t}) \]
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Budget constraint:
\[ c_{j,t} + s_{j,t} = w_{j,t} \]
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Budget constraint:

\[ c_{j,t} + s_{j,t} = w_{j,t} \cdot (1 - \tau_w). \]
Utility function:

$$u_t = \log(c_{j,t}) + \beta \log(\bar{R}s_{j,t}) - \nu(a).$$

Budget constraint:

$$c_{j,t} + s_{j,t} = w_{j,t} \cdot (1 - \tau_w) \cdot (1 - \eta).$$
Utility function:

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Budget constraint:

\[ c_{j,t} + s_{j,t} = w_{j,t} \cdot (1 - \tau_w) \cdot (1 - \eta) + T_j \]

Prettner and Strulik
Innovation, Automation, and Inequality 7 / 28
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Solution:

\[ c_{j,t} = \frac{(1 - \tau_w)(1 - \eta)w_{j,t} + T_j}{1 + \beta}, \quad s_{j,t} = \frac{\beta(1 - \tau_w)(1 - \eta)w_{j,t} + T_j}{1 + \beta}. \]
Individually invest in higher education if:

$$\nu(a) \leq (1 + \beta) \log \left[ \frac{(1 - \tau_w)(1 - \eta)w_{H,t} + T_H}{(1 - \tau_w)w_L + T_L} \right] \equiv \tilde{w}_t,$$

Figure 2: The Education Threshold
Final goods production:

\[ Y_t = \]
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\[ Y_t = \left( L_{L,t}^\alpha + \right) \]
Final goods production:

\[ Y_t = \left( L_L^\alpha, t + \sum_{i=1}^{A_t} X_i^\alpha, t \right) \]
Final goods production:

\[ Y_t = \left( L_{L,t}^\alpha + \sum_{i=1}^{A_t} X_{i,t}^\alpha \right) L_{H,Y,t}^{1-\alpha}. \]
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Factor rewards:

\[ w_{H,Y,t} = (1 - \alpha) L_{-H,Y,t} - \alpha L_{H,Y,t} \left( L_{L,t}^\alpha + \sum_{i=1}^{A_t} X_{i,t}^\alpha \right). \]
Final goods production:

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Factor rewards:

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Final Goods Production

- Final goods production:

\[ Y_t = \left( L_{L,t}^\alpha + \sum_{i=1}^{A_t} x_{i,t}^\alpha \right) L_{H,Y,t}^{1-\alpha}. \]

- Factor rewards:

\[
\begin{align*}
w_{H,Y,t} &= (1 - \alpha)L_{H,Y,t}^{-\alpha} \left( L_{L,t}^\alpha + \sum_{i=1}^{A_t} x_{i,t}^\alpha \right) = (1 - \alpha) \frac{Y_t}{L_{H,Y,t}}, \\
w_{L,t} &= \alpha \left( L_{H,Y,t}/L_{L,t} \right)^{1-\alpha},
\end{align*}
\]
Final Goods Production

- Final goods production:

\[ Y_t = \left( L_{L,t}^\alpha + \sum_{i=1}^{A_t} X_{i,t}^\alpha \right) L_{H,Y,t}^{1-\alpha}. \]

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\[ w_{L,t} = \alpha \left( L_{H,Y,t}/L_{L,t} \right)^{1-\alpha}, \]

\[ (1 + \tau_R)p_{i,t} = \alpha L_{H,Y,t}^{1-\alpha} X_{i,t}^{\alpha-1}. \]
- New blueprints for machines:

\[ A_{t+1} - A_t = \tilde{\delta}_t L_{H,A,t} \]

- R&D productivity:

\[ \tilde{\delta}_t = \frac{\delta A_t^\phi}{L_{H,A,t}^{1-\lambda}} \Rightarrow g_{A_{t+1}} = \delta A_t^{\phi-1} L_{H,A,t}^\lambda - 1. \]

Labor market clearing:

\[ L_{H,t} = L_{H,Y,t} + L_{H,A,t} \quad \text{and} \quad w_{H,A,t} = w_{H,Y,t}. \]

Implicit solution for labor employed in R&D:

\[ \tilde{R} \left[ \frac{\alpha^2}{\tilde{R}(1 + \tau_R)} \right]^{\frac{1}{1-\alpha}} \left( L_{H,t} - L_{H,A,t} \right) \delta A_{t-1}^{\phi} \frac{\hat{A}_t}{L_{H,A,t}^{1-\lambda}} = \]

\[ = \left( \frac{L_{L,t}}{L_{H,t} - L_{H,A,t}} \right)^{\alpha} + \tilde{A}_t \left[ \frac{\alpha^2}{\tilde{R}(1 + \tau_R)} \right]^{\frac{\alpha}{1-\alpha}}. \]

From there, everything can be solved recursively.

⇒ Analytical results to replicate the stylized facts.
⇒ Numerical results for redistribution policies.
Results: Existence and Uniqueness

Proposition (Existence and Uniqueness)

At any time $t$, the equilibrium employment level in the R&D sector exists and it is positive and unique. The long-run growth rate rises with employment in R&D and the standard driving forces of growth.

- The model encompasses the standard results of Romer (1990).
Proposition (Long-Run Growth)

- Technological progress is skill-biased.
- High-skilled wages rise with growth, low-skilled wages stagnate.
- Faster growth implies higher wage inequality.

This is consistent with the experience in the US. (Acemoglu and Autor, 2012; and Piketty, 2014).
Proposition (Labor Share)

The overall labor share is declining towards $(1 - \alpha)$. The low-skilled labor share is declining towards zero.

- Low-skilled workers do not benefit from new machines. Income stream of new machines flows to investors.
  
  ⇒ Model prediction is consistent with empirical findings by Elsby et al. (2013) and Karabarbounis and Neiman (2014).
Results: Wealth Inequality

Proposition (Wealth Inequality)

With economic growth, wealth concentration is increasing.

- Share of wealth held by high-skilled workers is given by

\[
\tilde{s} = \frac{(1 - \eta)(1 - \alpha) \frac{Y_t}{L_{H,Y,t}}}{(1 - \eta)(1 - \alpha) \frac{Y_t}{L_{H,Y,t}} + \alpha \left( \frac{L_{H,Y,t}}{L_{L,t}} \right)^{1-\alpha} \frac{L_{L,t}}{L_{H,t}}}
\]

- This is consistent with the data of Piketty (2014) and Alvaredo et al. (2017).
Results: Skill Upgrading

Proposition (Skill upgrading)

*With technological progress, the share of high-skilled labor in the population increases and converges towards $1 - \bar{a}.*

- The Race between Education and Technology: People try to upgrade their skills to escape wage stagnation and benefit from development.

- This is consistent with Goldin and Katz (2009) and Acemoglu and Autor (2012).
Numerical Analysis. Calibration

- Normalization: \( L = 1000 \),
- \( \phi < 1 \) (Jones case),
- Generation length: 25 years (starting 1950),
- \( \bar{R} = 1/\beta = 2 \) (4.5 percent p.a.),
- \( \alpha = 0.6 \) (long-run labor share 0.4),
- \( \eta = 5/(63 - 19) = 0.11 \),
- \( \bar{a} = 0.5 \).
- End of 20th century:
  - TFP growth rate 2 percent p.a.,
  - 30 percent college degree,
  - Skill premium of about 90%.

\[ \Rightarrow A(0) = 8, \psi = 2, \theta = 10, \lambda = 0.2, \text{ and } \delta = 0.43. \]
Simulation Results

Figure 3: Fit of the Model to the Evolution of Important Variables
Figure 4: Redistribution Policy to the Poor (green: $\tau_R = 0.05$; red: $\tau_W = 0.103$)
Figure 5: Education Subsidy (green: $\tau_R = 0.05$; red: $\tau_W = 0.103$)
Conclusions

R&D-based growth in the age of automation could lead to:
- declining labor income share,
- rising (income and wealth) inequality,
- increasing share of college-educated workers.

Low ability types would lose the race against the machine.

Potential solutions:
- Raising abilities.
- Means-tested basic income.
- Provide workers with a stake in firms via shares.
- Progressive consumption tax.
Thank you for your attention!
Extension: Automation and Technological Unemployment:

- So far: workers do not become unemployed.
- Akerlof and Yellen’s (1990) fair wage theory.
- Effort at work $e_j$ is given by $e = \min \left( \frac{w_j}{w_j^*}, 1 \right)$, where $w_j^*$ is the wage that is perceived as fair.
- Both types of workers only meet in production. Therefore:

$$Y_t = \left( e_{H,t} \cdot L_{H,t} \right)^{1-\alpha} \left[ \left( e_{L,t} \cdot L_{L,t} \right)^\alpha + \sum_{i=1}^{A_t} x_{i,t}^\alpha \right].$$
Fair wage of group $j$ is a weighted average of the wage received by the reference group and the market-clearing wage

$$w_{L,t}^* = \mu w_{H,t} + (1 - \mu)w_{L,t}^c, \quad w_{H,t}^* = \mu w_{L,t} + (1 - \mu)w_{H,t}^c,$$

where $\mu$ measures the strength of wage comparisons.

Let $\bar{L}_{j,t}$ denote labor supply of group $j$. We then have

$$w_{H,t}^c = (1 - \alpha)(\bar{L}_{H,t})^{-\alpha}(L_{L,t}^\alpha + \tilde{A}_t x_t^\alpha), \quad w_{L,t}^c = \alpha\bar{L}_{H,t}^{1-\alpha} (\bar{L}_{L,t})^{\alpha-1}.$$

High-skilled workers receive a wage that always exceeds the wage they perceive as fair.
The inverse demand function for low-skilled labor is given by

\[ w_{L,t} = \alpha (\bar{L}_{H,t})^{\alpha} \bar{L}_{L,t}^{\alpha-1} \equiv L_D(w_{L,t}). \]

Using \( w_{H,t} = w_{H,t}^c \) provides the “fair wage constraint”, i.e., the wage at which low-skilled workers exert full effort:

\[ w_{L,t} = \mu (1 - \alpha) (\bar{L}_{H,t})^{-\alpha} (\bar{L}_{L,t}^{\alpha} + \tilde{A}_t x_t^{\alpha}) \]
\[ + (1 - \mu) \alpha (\bar{L}_{H,t})^{1-\alpha} (\bar{L}_{L,t})^{\alpha-1} \equiv F_w(w_{L,t}). \]
Unemployment is given by $\bar{L}_L,0 - L_{L,0}$.

Technological progress shifts the fair wage constraint $F_W$ upwards and the low-skilled workforce $\bar{L}_L$ inwards.
Proposition (Technological Unemployment)

Once higher education converged towards its upper bound, more innovation and faster economic growth lead to more involuntary unemployment.

- If wages of high-skilled individuals rise further, this cannot anymore induce more people to attain college.
- Only the fair wage constraint shifts upwards and unemployment rises.
- From that point onwards, low-skilled workers unambiguously lose the race against the machine.
Figure 7: Technological Unemployment (green: $\tau_R = 0.05$; red: $\tau_W = 0.103$)