Robots or Workers?
A Macro Analysis of Automation and Labor Markets

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The rising threat of automation

- Fears that robots might displace jobs triggered policy debate (e.g., UBI)

- But automation doesn’t necessarily reduce aggregate employment: as old tasks are automated, new tasks get created (e.g., Autor 2015; Acemoglu and Restrepo 2018)

- Did automation depress wages while boosting employment during the long expansion prior to COVID-19?
  - Answers can also inform post-pandemic labor market recovery
What we do

- Examine GE impacts of the threat of automation on U.S. labor market: wage growth and employment
- Generalize DMP model to incorporate automation decisions
  - Consumption goods can be produced with workers or robots
  - An unfilled vacancy can be automated at a fixed cost drawn from i.i.d. distribution
  - Adopt a robot if fixed cost below benefit $\rightarrow$ endogenous prob of automation
- Our approach requires departure from textbook DMP model with free-entry; instead, vacancy creation is costly $\rightarrow$ unfilled vacancy has value (Leduc-Liu, 2020 AEJ Macro)
Theoretical insights

- Automation has both job-displacing and job-creating effects
  - Robots can substitute for workers in production (“robots” a metaphor for labor substituting technologies, different from traditional capital)
  - But option to automate raises vacancy value, boosting job creation
- Threat of automation raises firm reservation value, weakening worker bargaining power and pushing down wages: endogenous wage rigidity
  - Wage rigidities key for explaining large U fluctuations (e.g., Christiano, Eichenbaum, Trabandt, 2020)
- Increased automation also raises productivity, which, along with muted wage changes, amplifies U fluctuations
Quantitatively implications

- Estimate model to fit time series of $U$, $v$, wage, and productivity
  - Fitting productivity and wage data helps discipline model parameters and shocks

- The automation channel is quantitatively important
  1. for amplifying fluctuations in unemployment and vacancies
  2. for depressing wages while boosting productivity
  3. Absent automation channel, the Shimer volatility ratio (i.e., $\text{std}(v/u)/\text{std}(w)$) would have been 10, much smaller than data (39)

- Search frictions and automation both important for explaining labor market fluctuations
### Labor market

- **Job seekers**

  \[ u_t = 1 - (1 - \delta_t)N_{t-1} \]

  where \( \delta_t \) denotes job separation rate and \( N_{t-1} \) is beginning-of-period employment

- **Vacancies**

  \[ v_t = (1 - q^v_t)(1 - q^a_t)v_{t-1} + \delta_t N_{t-1} + \eta_t \]

  where \( q^v_t \) denotes job filling rate, \( q^a_t \) denotes automation probability, and \( \eta_t \) denotes newly created vacancies

- **Vacancy** is a slow-moving state variable: different from standard DMP with free entry
Matching technology

\[ m_t = \mu u_t^\alpha v_t^{1-\alpha} \]

Aggregate employment dynamics

\[ N_t = (1 - \delta_t) N_{t-1} + m_t \]

End-of-period unemployment rate

\[ U_t = u_t - m_t = 1 - N_t \]

Job filling and finding rates

\[ q_t^v = \frac{m_t}{v_t}, \quad q_t^u = \frac{m_t}{u_t} \]
A firm produces $y_t$ units of consumption goods using either a worker or a robot.

$$y_t = \begin{cases} 
Z_t & \text{if using one worker} \\
Z_t \zeta_t & \text{if using one robot}
\end{cases}$$

Aggregate output: sum of goods produced by $N$ workers and $A$ robots

$$Y_t = Z_t N_t + Z_t \zeta_t A_t$$

Stock of automation ($A_t$)

$$A_t = (1 - \rho^o)A_{t-1} + q^a_t (1 - q^v_{t-1}) v_{t-1}$$

where $\rho^o$ denotes obsolescence rate.
Vacancy creation

- Creating a new vacancy incurs an entry cost $e$ drawn from i.i.d. distribution $F(e)$
- Benefit of creating a vacancy is the vacancy value $J_t^V$
- New vacancy created if net value of entry is non-negative ($e \leq J_t^V$)
- Number of new vacancy being created

$$\eta_t = F(J_t^V)$$
Adopting robot incurs fixed cost \( x \) drawn from i.i.d. distribution \( G(x) \)

Net benefit of automation = value of robot net of value of foregone vacancy

\[
x_t^* = J_t^a - J_t^v
\]

Value of a robot

\[
J_t^a = \mathcal{Z}_t \zeta_t - \kappa_a + (1 - \rho^o) E_t D_{t,t+1} J_{t+1}^a
\]

where \( \kappa_a \) is flow cost of operating robots and \( D_{t,t+1} \) is SDF

Automate if \( x \leq x_t^* \) \( \Rightarrow \) prob of automating

\[
q_t^a = G(x_t^*)
\]
Values of an open vacancy and a filled position

- Value of an open vacancy ($J^\nu_t$)
  \[ J^\nu_t = -\kappa + q^\nu_t J^e_t + (1 - q^\nu_t) \mathbb{E}_t D_{t,t+1} \left[ q^a_{t+1} J^a_{t+1} + (1 - q^a_{t+1}) J^\nu_{t+1} \right] \]
  where $\kappa$ is vacancy posting cost

- Value of a filled position ($J^e_t$)
  \[ J^e_t = Z_t - w_t + \mathbb{E}_t D_{t,t+1} \left[ (1 - \delta_{t+1}) J^e_{t+1} + \delta_{t+1} J^\nu_{t+1} \right] \]
  where $w_t$ is wage rate
Representative household

- Utility function

\[ \mathbb{E} \sum_{t=0}^{\infty} \beta^t \Theta_t (\ln C_t - \chi N_t) \]

- Budget constraint

\[ C_t + \frac{B_t}{r_t} = B_{t-1} + w_t N_t + \phi(1 - N_t) + d_t - T_t \]

- Employment surplus

\[ S_t^H = w_t - \phi - \frac{\chi}{\Lambda_t} + \mathbb{E}_t D_{t,t+1}(1 - q_{t+1}^u)(1 - \delta_{t+1}) S_{t+1}^H \]
Wage determination

- Wages are determined by Nash bargaining

\[
\max_{w_t} \left( S_t^H \right)^b (J_t^e - J_t^\nu)^{1-b}
\]

- Steady state wage

\[
w^N = \phi + \frac{\chi}{\Lambda} + \frac{b}{1 - b} \left[ 1 - \beta (1 - q^u)(1 - \delta) \right] (J^e - J^\nu)
\]

- Wage increases with both worker reservation value \( \phi + \frac{\chi}{\Lambda} \) and worker bargaining weight \( b \)

- Wage decreases with firm reservation value \( J^\nu \)

- Threat of automation \( (q^a) \) raises \( J^\nu \) and thus lowers wage
Government policy and market clearing

- **Government policy**
  \[ \phi(1 - N_t) = T_t \]

- **Bond market clearing**
  \[ B_t = 0 \]

- **Final goods market clearing**
  \[ C_t + \kappa v_t + \kappa_a A_t + (1 - q_{t-1}^\nu) v_{t-1} \int_0^{x_t^*} xdG(x) + \int_0^{J_t^\nu} edF(e) = Y_t \]

- **Aggregate output**
  \[ Y_t = Z_t N_t + Z_t \zeta_t A_t \]
Empirical strategy

- Calibrate a subset of parameters to match SS observations
- Estimate remaining models parameters (in shock processes and in fixed cost distributions) using Bayesian methods
- Vacancy creation and robot adoption cost distributions
  
  \[ F(e) = \left( \frac{e}{\bar{e}} \right)^{\eta_v} \quad G(x) = \left( \frac{x}{\bar{x}} \right)^{\eta_a} \]

- Set \( \eta_v = \eta_a = 1 \)

- Estimate \( \bar{e}, \bar{x} \), and the shock parameters \( \rho_k \) and \( \sigma_k \), for \( k \in \{\theta, \zeta, z, \delta\} \)

- Fit model to time series of unemployment, vacancies, real wage growth, and average labor productivity growth (1985:Q1-2018:Q4)
### Steady state and calibrated parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta$</td>
<td>Subjective discount factor</td>
<td>0.99</td>
</tr>
<tr>
<td>$\phi$</td>
<td>Unemployment benefit</td>
<td>0.25</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>Elasticity of matching function</td>
<td>0.50</td>
</tr>
<tr>
<td>$b$</td>
<td>Nash bargaining weight</td>
<td>0.50</td>
</tr>
<tr>
<td>$\rho^\circ$</td>
<td>Automation obsolescence rate</td>
<td>0.03</td>
</tr>
<tr>
<td>$\kappa_a$</td>
<td>Flow cost of automated production</td>
<td>0.98</td>
</tr>
<tr>
<td>$\bar{\delta}$</td>
<td>Job separation rate</td>
<td>0.10</td>
</tr>
<tr>
<td>$\mu$</td>
<td>Matching efficiency</td>
<td>0.66</td>
</tr>
<tr>
<td>$\kappa$</td>
<td>Vacancy posting cost</td>
<td>0.09</td>
</tr>
<tr>
<td>$\chi$</td>
<td>Disutility of working</td>
<td>0.73</td>
</tr>
</tbody>
</table>

- Average unemployment rate from 1985-2018: $U = 0.06$
- Quarterly average job separation rate (JOLTS): $\bar{\delta} = 0.1$
- Quarterly job filling rate (den Haan et al, 2000): $q^\nu = 0.71$
- Vacancy posting costs (Leduc-Liu, 2019): $\kappa \nu = 0.01Y$
## Estimation results

<table>
<thead>
<tr>
<th>Parameter description</th>
<th>Posterior</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>5%</td>
</tr>
<tr>
<td>$\bar{\sigma}$ scale for vacancy creation cost</td>
<td>9.57</td>
</tr>
<tr>
<td>$\bar{x}$ scale for robot adoption cost</td>
<td>2.43</td>
</tr>
<tr>
<td>$\rho_z$ AR(1) of neutral technology shock</td>
<td>0.97</td>
</tr>
<tr>
<td>$\rho_\theta$ AR(1) of discount factor shock</td>
<td>0.98</td>
</tr>
<tr>
<td>$\rho_\delta$ AR(1) of separation shock</td>
<td>0.94</td>
</tr>
<tr>
<td>$\rho_\zeta$ AR(1) of automation-specific shock</td>
<td>0.76</td>
</tr>
<tr>
<td>$\sigma_z$ std of tech shock</td>
<td>0.01</td>
</tr>
<tr>
<td>$\sigma_\theta$ std of discount factor shock</td>
<td>0.01</td>
</tr>
<tr>
<td>$\sigma_\delta$ std of separation shock</td>
<td>0.05</td>
</tr>
<tr>
<td>$\sigma_\zeta$ std of automation-specific shock</td>
<td>0.04</td>
</tr>
</tbody>
</table>

- Estimation implies that 24% jobs are performed by robots in steady state, in line with empirical literature (e.g., Nedelkoska and Quintini, 2018)
Discount factor shock raises productivity, reduces wages and labor share.

[Graphs showing the effects of the discount factor shock on various economic indicators: Unemployment, Vacancy, Automation probability, Productivity, Wage, Labor share over time.]
Automation shock boosts productivity but depresses wages and labor share

Leduc and Liu (FRBSF)
Automation threat more powerful amplification than reducing worker bargaining power ($\theta$ shock)

- Automation mechanism important for countercyclical labor share

Benchmark No automation Low bargaining power
Model mechanism depends on both automation and labor search frictions ($\zeta$ shock)

- Job displacing dominates job creation with low search frictions
Automation and labor search frictions both important for explaining Shimer (2005) volatility puzzle

<table>
<thead>
<tr>
<th>Model</th>
<th>Labor market tightness</th>
<th>Real wage</th>
<th>Relative volatility</th>
</tr>
</thead>
<tbody>
<tr>
<td>Benchmark/Data</td>
<td>1.16</td>
<td>0.03</td>
<td>39.47</td>
</tr>
<tr>
<td>No automation</td>
<td>0.30</td>
<td>0.03</td>
<td>9.56</td>
</tr>
<tr>
<td>Low search friction</td>
<td>0.99</td>
<td>0.03</td>
<td>29.48</td>
</tr>
</tbody>
</table>
Plant-level evidence: more automated manufacturing establishments have higher labor productivity, smaller fraction of high-wage workers, and smaller labor share (Dinlersoz and Wolf, 2018)

Occupation-level evidence: occupations at higher risks of automation have lower wage growth (Arnoud, 2018)

International industry-level evidence: robot adoptions boost productivity, with much smaller positive effects on wages (Graetz and Michaels, 2018)

U.S. industry-level evidence: robot adoptions boost productivity but reduce local employment and wages (Acemoglu and Restrepo, 2020)
Conclusion

- We incorporate automation decisions in a DMP framework, and obtained a few insights
  - Threat of automation raises firms’ reservation value in wage bargaining, reducing wages
  - Automation amplifies fluctuations in unemployment and vacancies
  - Automation boosts productivity and depresses wages: a powerful amplification mechanism for labor market fluctuations

- Extensions and open questions:
  - Worker heterogeneity (e.g., skilled vs unskilled): How does automation affect income distribution and welfare? What’s optimal policy?
  - Pandemic uncertainty: Could it stimulate automation? How would automation affect labor market recovery? (Leduc-Liu, 2020)