Technology, Skill and the Wage Structure

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Discussion by
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Motivation

• Great paper
Motivation

- Great paper
- Rich yet tractable theoretical framework
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- Rich yet tractable theoretical framework
- Yields a sharp analytical characterization of the effects of task-specific changes in technology
Task-based Approach

- **Task-based approach** to the labor market versus **canonical model** of skilled/unskilled (Acemoglu and Autor 2011)
  - A *task* is a unit of work activity that produces output (goods and services)
  - A *skill* is a worker’s endowment of capabilities for performing various tasks
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- New technologies typically complement or substitute for particular tasks in a pattern that can be poorly summarized by aggregate measures of skills (college degree or equivalent)
  - Luddites: 19th-century English textile workers
  - Information and computing technology (ICT)
• Employment-weighted mean of DOT task percentiles across occupations

autor, levy and murnane (2003)

Figure I: Trends in Routine and Nonroutine Task Input, 1960 to 1998

Figure I is constructed using Dictionary of Occupational Titles [1977] task measures by gender and occupation paired to employment data for 1960 and 1970 Census and 1980, 1990, and 1998 Current Population Survey (CPS) samples. Data are aggregated to 1120 industry-gender-education cells by year, and each cell is assigned a value corresponding to its rank in the 1960 distribution of task input (calculated across the 1120, 1960 task cells). Plotted values depict the employment-weighted mean of each assigned percentile in the indicated year. See Table I and Appendix 1 for definitions and examples of task variables.

precomputer era—the upward trend in each accelerated thereafter. By 1998, nonroutine analytic task input averaged 6.8 centiles above its 1970 level and nonroutine interactive input averaged 11.5 centiles above its 1970 level. By contrast, the share of the labor force employed in occupations intensive in routine cognitive and routine manual tasks declined substantially. Between 1970 and 1998, routine cognitive tasks declined 8.7 centiles and routine manual tasks declined by 4.3 centiles. Notably, these declines reversed an upward trend in both forms of routine task input during the 1960s. For routine cognitive tasks, this trend reversed in the 1970s, and for routine manual tasks, the trend halted in the 1970s and reversed in the 1980s.
Michaels, Rauch and Redding (2016)

- Cumulative distributions of 1880, 1940 and 2000 employment across DOT occupation task percentiles

Note: On the horizontal axis, occupations are sorted according to their percentile of the occupation task distribution, as measured using the numerical scores from the Dictionary of Occupational Titles (DOTs) for 1991. “non-routine” is (non-routine analytic + non-routine interactive)/2; “routine” is (routine cognitive + routine manual)/2; and “manual” is non-routine manual. The vertical axis shows the cumulative share of the sorted occupations in total employment in each year. Occupation employment is measured using the IPUMs population census data for each year.
Model

• Final good produced using tasks

\[ y_F = \left( \sum_{j=1}^{J} (N\gamma_j)^{\frac{\rho - 1}{\rho}} y_j^{\frac{\rho}{\rho - 1}} \right)^{\frac{\rho}{\rho - 1}} \]

• Tasks produced with skill \( h \) and technology \( x \)

\[ y_j = \int \ell_j(h)\phi(h, x_j)dh, \quad \text{all } j, \]

\[ \phi(h, x_j) \equiv \left[ \omega h^{\frac{\eta - 1}{\eta}} + (1 - \omega)x_j^{\frac{\eta - 1}{\eta}} \right]^{\frac{\eta}{\eta - 1}}, \quad \eta, \omega \in (0, 1). \]

• Production is log supermodular in technology and skill as in Costinot and Vogel (2010)
  – Additional CES structure on the productive technology
  – Discrete number of tasks
Theoretical Predictions

• Equilibrium exhibits Positive Assortative Matching (PAM) and can be characterized recursively
  – Skill thresholds $h_{\min} = b_0 < b_1 < \cdots < b_{J-1} < b_J = h_{\max}$
  – Technology $x_j$ employs workers in skill bin $j$ $(b_{j-1}, b_j)$

• Suppose that technical change increases technology $x_k$ by a small increment $\epsilon > 0$
  – Output increases and price falls for task $k$
  – Ripple effects that are dampened for more distant tasks
  – For $\rho = 1$, all skill thresholds shift upward (task downgrading for some workers)
  – For $\rho > 1$, thresholds at and above $k^{th}$ shift upward, while those at and below $(k - 1)^{th}$ can shift either way
  – For $\rho < 1$, thresholds at and below $(k - 1)^{th}$ shift upward, while those at and above $k^{th}$ can shift either way
  – Determine employment, output, price and wage effects

• Quantitative empirical evidence on these predictions?
Roy Model

- Related formulation in terms of a Roy model
  - Hsieh, Hurst, Klenow and Jones (2013), Burstein, Morales and Vogel (2016) and Michaels, Rauch and Redding (2016)
- Indirect utility depends on wage per effective unit of labor, idiosyncratic ability draw and cost of living

\[ U_{so}(i) = \frac{w_{so}z_{so}(i)}{P} \]

- Idiosyncratic ability draw from Fréchet distribution

\[ F_{so}(z) = e^{-T_{so}z^{-\theta}}, \quad \theta > 1 \]

- Probability a worker chooses sector \( s \) and occupation \( o \)

\[ \pi_{so} = \frac{T_{so}w_{so}^\theta}{\sum_{r=1}^{S} \sum_{m=1}^{O_s} T_{rm}w_{rm}^\theta} \]
Existing Evidence

• Burstein, Morales and Vogel (2016) quantitative decomposition of changes in between-group inequality
  – Computerization and shifts in occupation demand account for roughly 80 percent of the rise in the skill premium
  – Computerization alone accounts for roughly 60 percent

• Hsieh, Hurst, Jones and Klenow (2013) use Roy model to quantify changes in misallocation across occupations
  – Around 15-20 percent of growth in aggregate output per worker explained by improved allocation of talent

• Connection between the model and evidence on between-firm changes in wage inequality
  – Helpman, Itskhoki, Muendler and Redding (2016)
  – Song, Price, Guvenen, Bloom and Wachter (2016)
  – Embed assignment model in Melitz firm heterogeneity framework (Sampson 2014)
Comments

- Great paper

- Flexible and tractable framework

- Sharp analytical results for the general equilibrium impact of technical change for a limited set of tasks

- Interesting to provide evidence on the quantitative magnitude of these effects in the data