

Automation and Labor Demand: Estimating Task Based Models with Microeconomic Data

A large, faint watermark of the University of Chicago crest is visible in the background. It features an eagle with spread wings perched on a laurel wreath, with an open book above it containing the Latin motto "VERITAS EXCOLATUR".

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Introduction



Research Question

How do current task based models of labor automation preform against empirical evidence at the firm level?

Motivation:

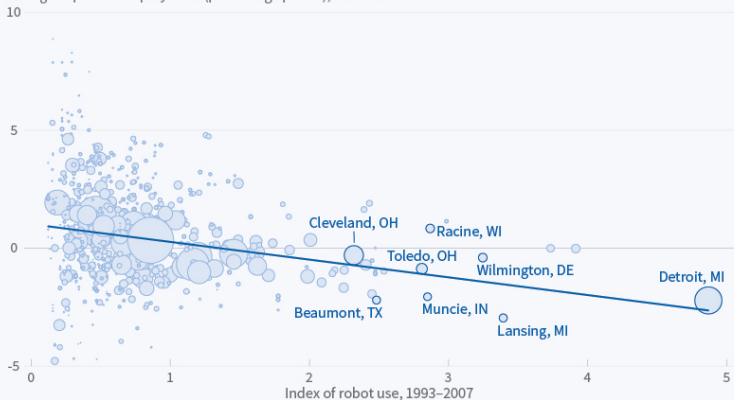
- Rising productivity/declining labor share
 - “Labor will become less and less important... More and more workers will be replaced by machines. I do not see that new industries can employ everybody who wants a job” - Wassily Leontief, 1952
- Trade vs. Automation and policy questions
- “Future of Work”
- Firm-level data

Declining Labor Share



Employment and Exposure to Robots

Change in private employment (percentage points), 1990–2007



Larger circles denote larger commuting zones

Source: Researchers' calculations using International Federation of Robotics, U.S. Census, and other data



- Zeira (1998)
- Acemoglu and Autor (2011)
- Brynjolfsson and McAfee (2012)
- Acemoglu and Restrepo (2016)
- **Acemoglu and Restrepo (2017)**
 - Henceforth, (AR17)
 - Empirical
- **Acemoglu and Restrepo (2018)**
 - Task Based vs. Factor Augmenting



- Evaluation of task based model using firm-level data
- Revised empirical model specification to incorporate different data
- Structural estimation of parameters (GMM)
- Estimation of aggregate labor demand effect (Maybe)

Theoretical Model: Automation in Autarky (AR17)

CES Production:

$$Y_c = \left(\sum_{i \in \mathcal{I}} \alpha_i Y_{ci}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \text{ for } c \in \mathcal{C} \text{ and } \sum_{i \in \mathcal{I}} \alpha_i = 1$$

Supply of labor and robots with ϵ and η as elasticities of supply of labor and robots,

$$W_c = \mathcal{W}_c Y_c L_c^\epsilon, \epsilon \geq 0$$

$$Q_c = \mathcal{Q}_c \left(\frac{R_c}{Y_c} \right)^\eta, \eta \geq 0$$

Demand for labor satisfies:

$$d \ln L_c^d = - \sum_{i \in \mathcal{I}} l_{ci} \frac{dM_i}{1 - M_i} - \sigma \sum_{i \in \mathcal{I}} l_{ci} \ln P_{Xci} + d \ln Y_c$$

l_{ci} is share of employment in industry, i , in cz , c . M_i share of tasks automated. P_{Xci} is price of output X in industry, i , cz , c . σ denotes elasticity of substitution across goods produced in different industries.

Empirical Model (AR17)



Impact of robots on employment is given by,

$$d \ln L_c = -\frac{1+\eta}{1+\epsilon} \sum_{i \in \mathcal{I}} l_{ci} \frac{dM_i}{1-M_i} + \frac{1+\eta}{1+\epsilon} \pi_c \sum_{i \in \mathcal{I}} l_{ci} \frac{s_{icL}}{s_{cL}} \frac{dM_i}{1-M_i}$$

Where,

$$\sum_{i \in \mathcal{I}} \frac{s_{icL}}{s_{cL}} \frac{dM_i}{1-M_i} \approx \frac{1}{\gamma} \sum_{i \in \mathcal{I}} l_{ci} \frac{dR_i}{L_i} = \text{exposure to robots}$$

Then,

$$d \ln L_c = \beta_c^L \sum_{i \in \mathcal{I}} l_{ci} \frac{dR_i}{L} + \epsilon_c^L$$

Where,

$$\beta_c^L = \left(\frac{1+\eta}{1+\epsilon} \pi_c - \frac{1+\eta}{1+\epsilon} \right) \frac{1}{\gamma}$$

γ denotes productivity of labor ($\gamma > 0$). s_{icL} denotes share of labor in the output of industry i in commuting zone c . π_c is cost saving by substituting robots for labor. R_i is robot penetration in industry i .

Table: US Projects Data 1985-2015 - Conway

Date Entered	Firm Name	City	County	State	NAICS	Investment (\$ Million USD)	Jobs
31-12-2015	PUBLIX SUPER MARKETS, INC.	Orlando	Orange	FL	445110	16	48

Table: Concentration of industrial robots in all - Brookings

Metro Area	Total Industrial robots, 2010	Total Industrial robots, 2015
Elkhart-Goshen, IN	1778	4355

Table: County Level Returns - IRS

Year	FIPS	Number of Returns	Aggregate Wage (\$ USD Thousands)
2015	12095	1501130	129840547

Structural Estimation



Our model,

$$\ln L_j = \beta_j^L \sum_{m \in \mathcal{MSA}} l_{jm} \frac{R_m}{L_m} + \epsilon_m$$

Where $m \in \mathcal{MSA}$ represents a metropolitan statistical area, and j is a firm in the US projects data.

Procedure

1. Restrict to manufacturing sectors.
2. Merge firm data with robot exposure per MSA by MSA, and total labor in MSA.
3. Estimate β_j^L using a method of moments equating first two sample moments to theoretical moment.
4. Test robustness of estimation and attempt to estimate aggregate effect from parameters (Interpret parameters).

⇒ **firm level** gain from substitution of automation for labor.

Expected Problems/Future Work



Problems

- Date of Entry in Conway Data is inaccurate
- Conway data may not be complete enough
- How to interpret β and test against aggregate level results

Future (of) Work

- How can we revise macro models of automation to learn about micro-level phenomena?
- What can we learn/predict about the future of work from micro-level insight?
- 2SLS to test for causal effect of robot exposure on labor demand