

Robots, Firms, and Workforce Composition

Deng, Mueller, Plümpe & Stegmaier

Discussion by Simon Bunel (*Banque de France and PSE*)
CompNet ProdTalk - 10 May 2022

Any opinions and conclusions expressed in this discussion do not necessarily represent the views of the Banque de France.

This paper: What it does

- Study the impact of robot adoption on employment composition at plant-level in Germany
- Build a task-based model as in Acemoglu and Restrepo (2018) to derive some theoretical predictions
- Exploit plant-level data to empirically test these predictions combining:
 - ▶ Robot use data
 - ▶ Employer-employee dataset (hiring, job separations, age and occupations)
- Event study design

This paper: What it finds

Theory - Task-based model:

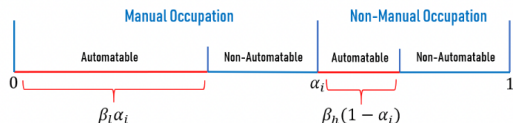


Figure 1: Automatable and Non-Automatable Tasks by Occupation

$$y_i = A_i \left(\underbrace{(\beta_l \alpha_i + \beta_h (1 - \alpha_i))^{\frac{1}{\sigma}} (\lambda k_i)^{\frac{\sigma-1}{\sigma}}}_{\text{robots}} + \underbrace{((1 - \beta_l) \alpha_i)^{\frac{1}{\sigma}} \ell_i^{\frac{\sigma-1}{\sigma}}}_{\ell\text{-labor}} + \underbrace{((1 - \beta_h)(1 - \alpha_i))^{\frac{1}{\sigma}} h_i^{\frac{\sigma-1}{\sigma}}}_{h\text{-labor}} \right)^{\frac{\sigma}{\sigma-1}}, \quad (3)$$

Empirics - Event-study design exploiting the timing of adoption of robots:

$$Y_{it} = \alpha_i + \sum_{t=-3}^{t=1} \beta_t T_t + \sum_{t=-3}^{t=1} \gamma_t \text{Robot}_i T_t + \epsilon_{it},$$

This paper: What it finds

Prediction 1: the employment effect is ambiguous and, if it is positive, it is accompanied with increased worker reallocation.

Empirical results:

- Positive effect on employment
- Positive effect on hiring and separations

	(1) Employment b/se	(2) Hirings b/se	(3) Separations b/se
2.rel_time	0.0056 -0.0035	-0.0780*** -0.0188	0.0298 -0.0187
3.rel_time	0.0090* -0.0048	-0.0501** -0.0197	0.0521*** -0.019
4.rel_time	0.0135** -0.0059	-0.0129 -0.02	0.0893*** -0.0195
5.rel_time	0.0072 -0.008	-0.0295 -0.0212	0.1167*** -0.0201
1.D_robot_adoption#2.rel_time	0.0094 -0.0101	0.0574 -0.0715	0.0027 -0.0621
1.D_robot_adoption#3.rel_time	0.0204 -0.0152	0.1002 -0.0763	0.0611 -0.061
1.D_robot_adoption#4.rel_time	0.0494** -0.0231	0.2697*** -0.0756	0.0549 -0.0672
1.D_robot_adoption#5.rel_time	0.0580** -0.0279	0.2029** -0.0796	0.1213* -0.0703

This paper: What it finds

Prediction 2: Occupations performing less automatable tasks will experience the strongest gains in employment.

Empirical results:

- Statistically significant increases in the employment of technicians/engineers and managers.

Table 4: Effects by occupation and age (event study results)

	Occupation					Age		
	(1) simple manual b/se	(2) qual manual b/se	(3) techn/engin b/se	(4) manager b/se	(5) svc occ b/se	(6) young b/se	(7) midage b/se	(8) older b/se
2.rel_time	0.0152** (0.0069)	0.0017 (0.0060)	0.0156*** (0.0060)	0.0053 (0.0055)	0.0029 (0.0065)	-0.0138* (0.0080)	-0.0055 (0.0049)	0.0505*** (0.0075)
3.rel_time	0.0187** (0.0095)	0.0049 (0.0078)	0.0290*** (0.0077)	0.0192*** (0.0071)	0.0126 (0.0087)	-0.0179* (0.0106)	-0.0149** (0.0066)	0.1005*** (0.0098)
4.rel_time	0.0315*** (0.0117)	0.0051 (0.0096)	0.0439*** (0.0094)	0.0373*** (0.0088)	0.0247*** (0.0107)	-0.0264** (0.0126)	-0.0275*** (0.0081)	0.1616*** (0.0117)
5.rel_time	0.0411*** (0.0142)	-0.0130 (0.0122)	0.0458*** (0.0108)	0.0426*** (0.0105)	0.0219* (0.0121)	-0.0515*** (0.0147)	-0.0514*** (0.0107)	0.2014*** (0.0132)
1.D_robot_adoption#2.rel_time	0.0068 (0.0215)	0.0020 (0.0183)	0.0216 (0.0197)	0.0353 (0.0303)	0.0161 (0.0203)	0.0294 (0.0181)	-0.0037 (0.0130)	0.0459* (0.0247)
1.D_robot_adoption#3.rel_time	0.0165 (0.0290)	0.0461* (0.0278)	0.0066 (0.0299)	0.0243 (0.0359)	0.0213 (0.0312)	0.0653** (0.0277)	0.0110 (0.0208)	0.0346 (0.0259)
1.D_robot_adoption#4.rel_time	0.0097 (0.0491)	0.0662 (0.0445)	0.0669* (0.0357)	0.0740* (0.0412)	0.0715 (0.0489)	0.1098*** (0.0338)	0.0441 (0.0282)	0.0196 (0.0370)
1.D_robot_adoption#5.rel_time	0.0225 (0.0578)	0.0841 (0.0560)	0.0841** (0.0389)	0.0990** (0.0483)	0.0887 (0.0542)	0.1449*** (0.0412)	0.0568* (0.0334)	0.0284 (0.0408)

This paper: What it finds

Prediction 3: The impact of robot adoption on employment in different age groups varies systematically with occupation.

Empirical results:

- Positive impact for younger workers in the firm.
- Effect more + for (i) simple manual tasks for young workers, (ii) technicians and engineers for middle aged workers and (iii) managers for older workers.

Table 4: Effects by occupation and age (event study results)

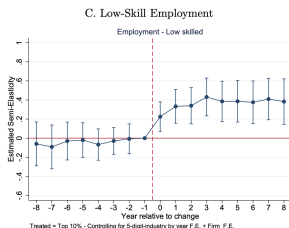
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Main Comment

- Important paper on the impact of technical change on employment, at the intersection of several other contributions in the literature:
 - ▶ Demographic/occupational research question following Acemoglu and Restrepo (2022)
 - ▶ Using micro (plant) data (Aghion et al. (2022) among many others)
 - ▶ On robot use (Koch et al. 2021)
 - ▶ In the German context (Dauth et al., 2021)
- Very interesting dialogue between theory and empirics to derive some results about the impact of robots on workforce composition.

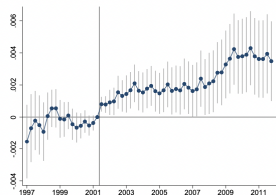
Main Comment

- Contributes to a new strand of the literature on complementarity/substituability between labor and capital:

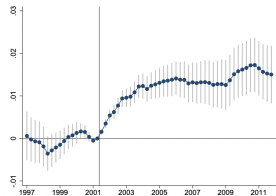


(a) Aghion et al. (2022)

(A) Fraction of Employees with High School Education or Less



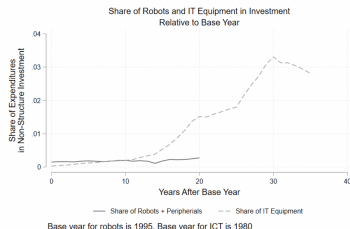
(B) Fraction of Employees 35 Years Old or Younger



(b) Curtis et al. (2022)

Comment: Is something special about robots?

- Advantage: identifies a specific and well-defined type of technology (ISO definition)
- Benmelech and Zator (2021):
 - ▶ Investment in robots accounts for less than 0.30% of aggregate expenditures on equipment
 - ▶ Recent increases in robotization do not resemble the explosive growth observed for IT technologies in the past.



- Consequence: Only 116 adopting firms in the sample
- What about a broader measure of modern manufacturing capital? (Aghion et al. 2022 / Curtis et al. 2022)

Comment: Endogeneity of robot adoption

- Could be interesting to have descriptive statistics about firm characteristics before adoption to understand what led them to adopt
- Pre-trends on "Young - simple manual tasks" or "Older - managers" could point in the direction of the existence of some confounding factors or, even, reverse causality

Comment: Heterogeneity within occupation

- Would be interesting to study empirically the impact on the type of tasks performed within occupation
- Might have reallocation at the task level but not at the occupation level