Automation and employment: preliminary evidence for Italian firms

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Labor market effects of AI/automation

Theoretical mechanisms

- Displacement effect (Automation replaces human tasks)
  - employment $\downarrow$
  - change in relative labor demand $\rightarrow$ some workers are more demanded
- Productivity and scale effects (Automation makes labor and capital more productive)
  - Employment expansion
  - Automation requires the creation of new (human) tasks
- Employee matching effect (Change in the profile of new hires)
  - Sorting: High wage workers attracted to better firms (AKM)

Labor market effects of AI/automation - Empirical evidence

Effects on employment

- *Aggregate studies* fail to find a consensus
  (Acemoglu et al., 2020; Acemoglu and Restrepo, 2017; Dauth et al., 2018; Graetz and Michaels, 2018; Klenert et al., 2020)
- *Firm-level studies* Recent evidence that shows increase in employment of adopters of automation/robots in France, Spain, and Netherlands
  (Acemoglu et al., 2020; Aghion et al., 2020; Bessen et al., 2020; Bonfiglioli et al., 2020; Domini et al., 2021b; Koch et al., 2019)

Effects on occupational structure

- Domini et al., 2021b do not find any effect of automation on share of different occupational categories in French firms

Effects on workers

- Bessen et al., 2019, using a Dutch survey on automation costs, find that automation leads to a higher probability of separation, especially for higher-skilled workers

Our contribution

- Provide first large-scale evidence on the effects of automation in Italian firms
- First (today), focus on effects on firm-level employment and occupational structure
- Then (to be done), investigate the effects on workers

Data sources

- ISTAT, International trade statistics, 2011-2019
- ISTAT, Statistical register "ASIA Occupazione" (2011-2019)
- ISTAT, FRAME-SBS register (2011-2019)

Sample definition

- Identification of importers in 2011-2019 (at least one importing transaction within the period)
- For this sample, employment (employees) and labour-force characteristics at firm-level are retrieved by Asia Occupazione (LEED structure)
- For this sample, economic and structural characteristics are retrieved by FRAME-SBS register
- After merging the different sources and after some cleaning, the sample of analysis is made of 201,408 firms (816,827 obs.)

Identifying and characterising automation and AI events

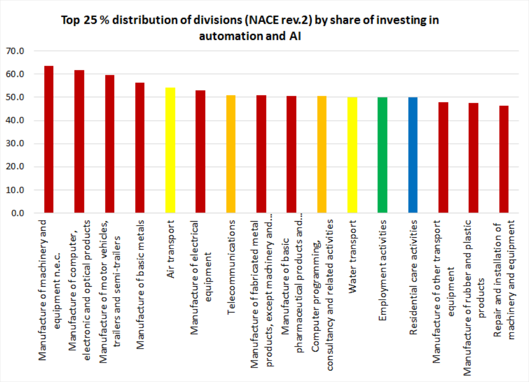
- We identify imported capital goods embedding automation and AI technologies via HS6 product codes appendix
  - We build on a taxonomy by Acemoglu and Restrepo (2018)
- Useful proxy since we lack systematic firm-level info on adoption of automation/AI technologies
  - Done by several studies (Acemoglu et al., 2020; Aghion et al., 2020; Bonfiglioli et al., 2020; Dixon et al., 2019; Domini et al., 2021b)
  - Exceptions: survey data (Bessen et al., 2019; Dinlersoz et al., 2018)
- Spiky behaviour typical of investment (cf. Domini et al. 2020): rare *across* firms and *within* firms
  $\rightarrow$ **Largest event** for each firm = automation/AI **spike**
- Firms adopting automation/AI are different from those who don't

Distribution of imports of automation/AI goods across sectors

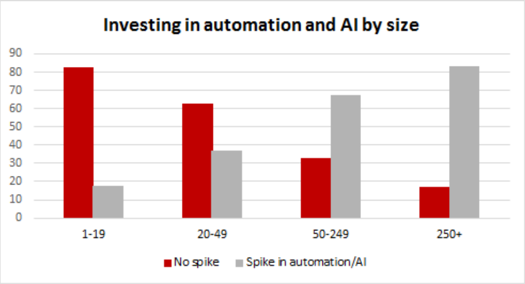
Table 1: Distribution of imports embedding automation technologies and employment across sectors, 2019

Digital intensity quartile	Share in imports embedding automation technologies (%) (1)	Share in total employment (%) (2)	Ratio (1)/(2)
High-medium tech manufacturing	26.1	25.4	1.03
Low-medium tech manufacturing	11.5	28.6	0.40
Knowledge intensive services	5.2	11.0	0.47
Lower knowledge intensive services	57.3	35.0	1.63

Distribution of adopting firms, top 25% sectors



Distribution of adopting firms across size categories



Characteristics of firms importing automation/AI goods

Table 2: Comparing firms with and without an automation/AI spike, all years (2011-2019)

	No spike	Spike	T-test
Number of employees	20.119	97.999	***
Value added per employee	76,663	87,252	***
Share of female employees (%)	42.337	31.659	***
Share of 15/29 years employees (%)	18.989	16.899	***
Share of blue-collars employee (%)	48.547	43.4667	***
Share of white-collars employee (%)	42.940	46.242	***
Share of managers (%)	0.610	1.485	***
Share of permanent employees (%)	85.639	89.2	***
Share of temporary employees (%)	14.360	10.799	***
Share of part-timers (%)	26.761	13.84	***
Number of observations	557,552	259,275	
Number of firms	160,341	41,067	

Automation/AI imports are rare within firms

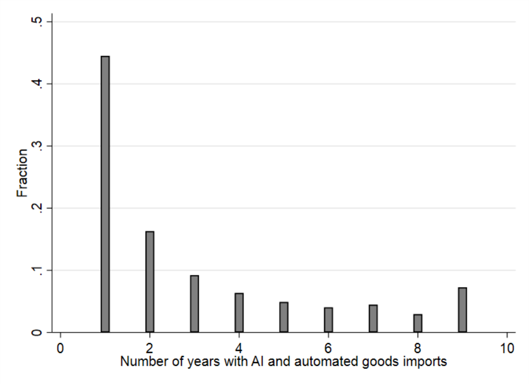


Figure 1: Number of years with imports of automation/AI goods

Spikes account for high share of investments within firms

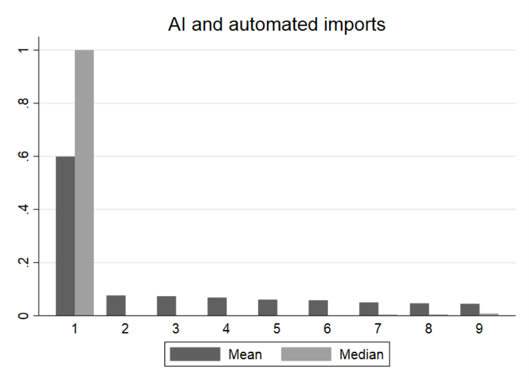


Figure 2: Investment shares by rank

Event Study Methodology

Spiky behaviour

event study (Bessen et al., 2020; Domini et al., 2021a)

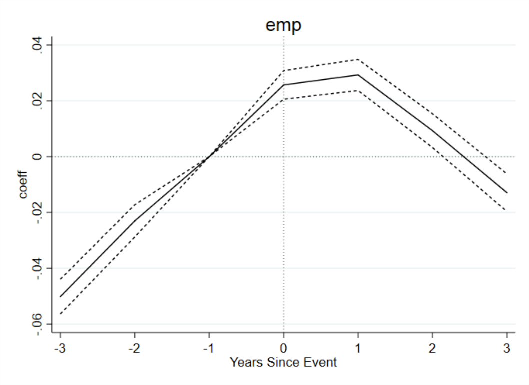
Selection into automation/AI

$$y_{ijt} = \sum_{k \neq -1; k_{min}}^{k_{max}} \beta_k D_{kit} + \delta_i + \zeta_{jt} + \varepsilon_{it} \tag{1}$$

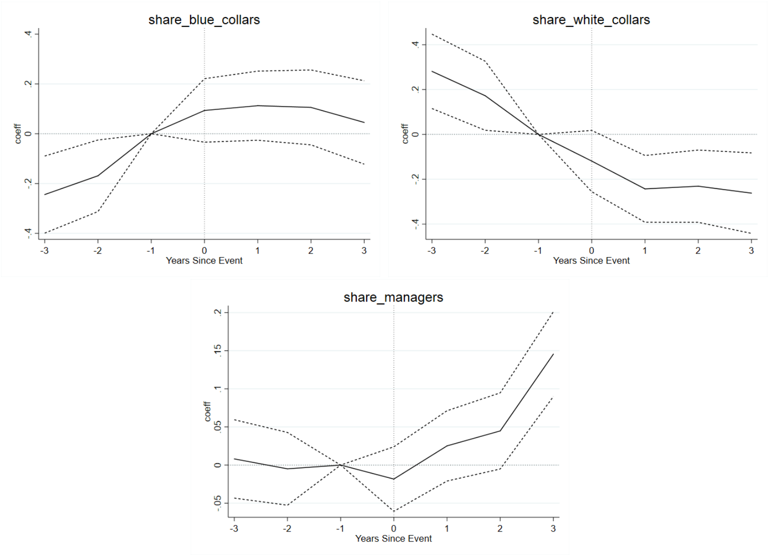
y_{ijt} is the dependent variable of interest for firm i at time t in sector j; D_{kit} is a dummy $= 1$ if index$=$ k for firm i in year t

Centered at $t-1$, so the coefficient on $t=0$ measures what happens in the year of the spike, with respect to the previous year

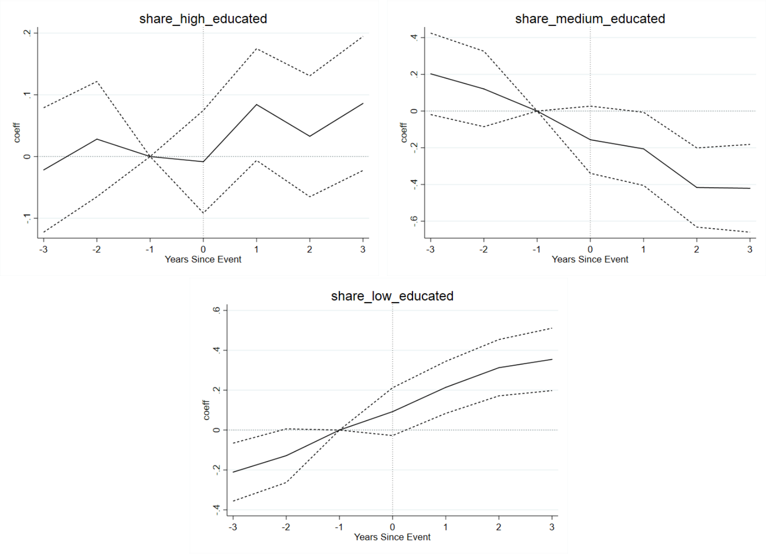
Employment



Occupational categories



Education


share_high_educated
coeff
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Years Since Event
share_medium_educated
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Years Since Event
share_low_educated
coeff
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Years Since Event

Concluding remarks

- First preliminary investigations on the effects of automation in Italian firms
- Automation spikes are followed by increase in employment, share of managers, and share of low educated workers
- Automation spikes are followed by decrease in white collars and medium educated workers
- To be done: account for pre-spike trend
- To be done: Investigate the effects on individual workers

Data appendix

Product codes (HS6) embedding relevant technologies

Label	HS-2012 codes
1. Industrial robots	847950
2. Dedicated machinery	847989
3. Automatic machine tools (incl. Numerically controlled machines)	845600-846699, 846820-846899, 851511-851519
4. Automatic welding machines	851521, 851531, 851580, 851590
5. Weaving and knitting machines	844600-844699, 844700-844799
6. Other textile dedicated machinery	844400-844590
7. Automatic conveyors	842831-842839
8. Automatic regulating instruments	903200-903299
9. 3-D printers	847780
10. Automatic data processing machines	847141-847150, 847321, 847330
11. Electronic calculating machines	847010-847029

Codes for (1)-(8) based on Acemoglu and Restrepo (2018, A-12-A14), for (9) on Abeliansky et al., 2015, p. 13, for (10)-(11) on ALP matching of USPC code 706 ('Data processing - Artificial Intelligence') to HS codes (Lybbert and Zolas, 2014) and own expertise.

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