Automation, firm-level employment and industry dynamics: new evidence from Italy

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Automation and employment: Empirical evidence

Effects on employment

- *Aggregate studies* report mixed evidence (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020; Klenert et al., 2020; Dauth et al., 2021)
- *Firm-level studies* Most recent evidence shows increase in employment of adopters of automation/robots in Canada, France, Germany, and Spain (Dixon et al., 2021; Acemoglu et al., 2020; Aghion et al., 2020; Domini et al., 2021; Benmelech and Zator, 2022; Koch et al., 2021)

  But: negative effects in Netherlands (Bessen et al., 2020)
- Coherent with previous evidence on process innovation and embodied technical change (Pianta, 2005; Calvino and Virgillito, 2018; Barbieri et al., 2020; Dosi and Mohnen, 2019)

Effects on occupational structure

- Similar mixed evidence: Domini et al. (2021, 2022) do not find any effect of automation on share of different occupational categories in French firms, neither on wage inequality; contra, Dixon et al. (2021) find evidence of polarisation

Automation and employment: evidence on Italy

Available evidence on Italy mostly concerns what happens to workers exposed to robots, not directly measuring the adoption at the firm level:

- Dottori (2021), using administrative and IFR data, shows that robots did not have a negative impact on local labor markets over the period 1990-2016; also positive effects on incumbent workers within firms in terms of longer working relationship and wage, but reallocation towards less robot intensive industries
- Faia et al. (2022), using administrative data, show that robot adoption affects sorting between workers and firms
- But Cirillo et al. (2023), using three waves of INAPP surveys and ORBIS: 3,000 firm-year observations followed over three years: 2010, 2014 and 2018. New digital technologies have a positive effect on sales, productivity, and wages

Our contribution

- We construct a novel database, integrating three different data sources (yearly):
  - ISTAT, International trade statistics (CoE), 2011-2019
  - ISTAT, Statistical register "ASIA Occupazione" (2011-2019)
  - ISTAT, FRAME-SBS register (2011-2019)
- Provide large-scale empirical evidence on the effects of automation within adopting firms using import of automation goods as well as implications on industry reallocation
- Not just robots, but effects of automation in general (similar to Aghion et al. (2020); Bessen et al. (2020); Dinlersoz et al. (2018)): automation may take many other forms and is only performed by robots in some work processes, for example, in the automotive industry, in welding, painting, and material handling (Krzywdzinski 2021)

Labour market effects of automation

Firm-level 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

Industry reallocation

- Adopting firms may grow at the expense of non-adopting firms (business stealing effect)

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 approximately 180,000 importing firms

Identifying and characterising automation events

- We identify imported capital goods embedding automation 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 and technologies
  - Done by several studies (Dixon et al., 2021; Bonfiglioli et al., 2020; Acemoglu et al., 2020; Aghion et al., 2020; Domini et al., 2021)
  - Exceptions: survey data (Bessen et al., 2020; 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 **spike**

Automation events - What are we measuring?

- The exercise captures firm-level effects that do not necessarily have an aggregate/sectoral equivalent -> Importance of sectoral exercises and controls for firm-heterogeneity
- Our measure do not map directly into the process/product innovation classification -> It is more likely associated with process innovation, but it can anticipate product innovation
- Indirect measures of automation are exposed to potential bias
  i) label adopters firms that trade but do not use automation goods;
  ii) label non-adopters firms adopting through other channels.
  - Firms may purchase automation goods domestically -> We limit the analysis to firms involved in international trade; estimates comparing adopters with not-yet-adopters
  - Firms may use an intermediary rather than direct import (Ahn et al., 2011; Bernard et al., 2010) -> This is less likely for more complex goods (Bernard et al., 2015) that are highly relation-specific.
  - Importers may resell in the domestic or international markets -> We remove intermediaries and firms importing every year. Carry along trade: run the analysis removing re-exporters.

Descriptive statistics

	TOTAL ECONOMY			MANUFACTURING		OTHER SECTORS	
Year	Importers FS	Importers ES	Automation Importers ES	Importers ES	Automation Importers ES	Importers ES	Automation Importers ES
2011	8.31	39.1	21.5	66.8	42.6	28.5	13.4
2012	8.44	38.4	21.2	67.4	43.3	27.9	13.2
2013	8.83	39.3	21.7	68.8	44.4	28.6	13.6
2014	9.07	39.8	22.0	69.3	45.1	29.2	13.8
2015	9.04	39.7	21.8	69.1	45.1	29.5	13.7
2016	9.03	39.7	21.8	69.1	45.2	29.7	13.8
2017	8.86	39.8	21.2	68.7	44.8	30.2	13.4
2018	8.70	39.7	21.0	68.6	44.8	30.2	13.1
2019	8.48	39.4	20.9	68.5	44.8	29.8	13.0

Table 1: Firms share (FS) and Employment share (ES) of importers and importers of automation for the whole economy, the manufacturing sector and the other sectors, in the time span 2011-2019. (%)

Distribution across sectors, 2019 - Employment

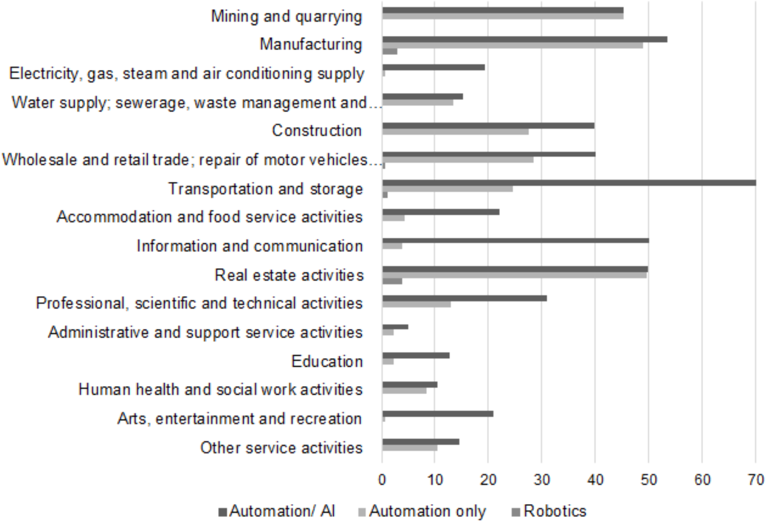
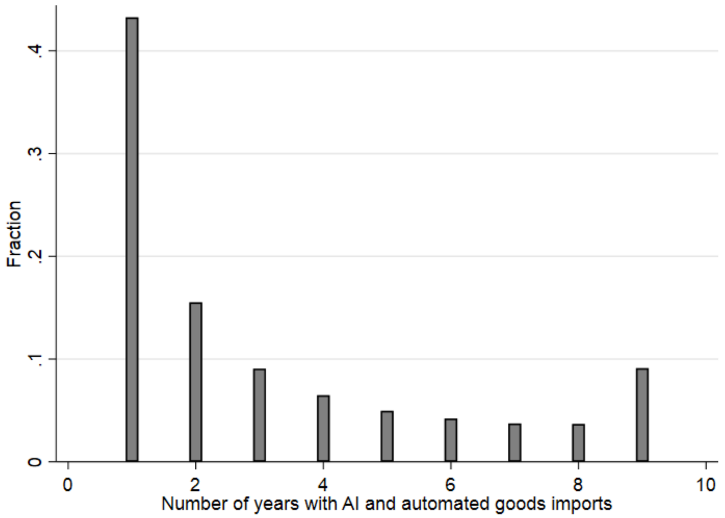


Figure 1: Share of employment
of automation importers

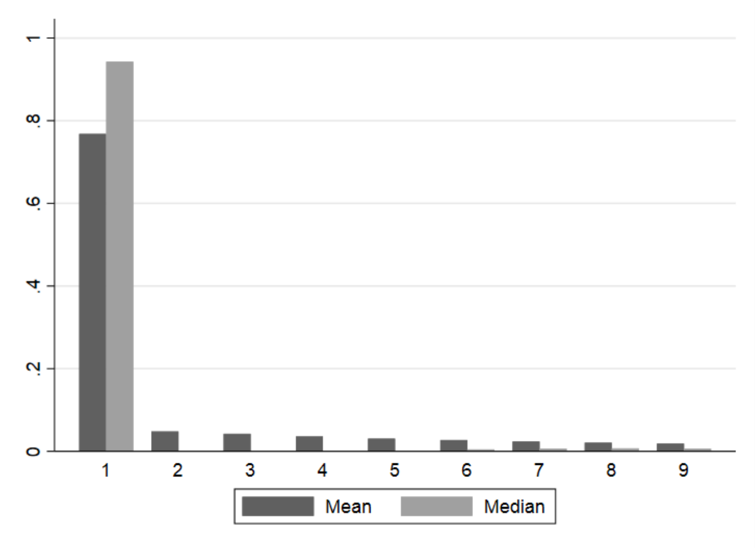
Automation imports are rare within firms

Figure 2: Number of years with positive imports of automation goods.



Spikes account for high share of investments within firms

Figure 3: Investment shares by rank.
Rank 1 is the highest yearly investment share in the firm's timeline.



Characteristics of firms importing automation goods

Firms adopting automation are different from those who don't

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

	No spike	Spike	T-test
Number of employees	19.88	102.99	***
Value added per employee	64,098	83,848	***
Share of blue-collars employee (%)	56.05	49.89	***
Share of white-collars employee (%)	41.59	44.85	***
Share of managers	1.85	4.77	***
Share of 15/29 years employees (%)	18.21	15.38	***
Share of permanent employees (%)	88.734	92.6835	***
Share of high-educated workers (%)	12.73	15.36	***
Share of part-timers (%)	27.65	13.71	***
Number of observations	985,185	244,197	
Number of firms	150,987	31,203	

Notes: ***: significant difference at 1% level.

Econometric Methodology

Spiky behaviour
Largest event of automation import as treatment variable (Bessen et al., 2020; Domini et al., 2021, 2022)

Difference-in-differences with multiple time periods:

- variation in treatment timing
- the "parallel trends assumption" holds potentially only after conditioning on observed covariates.
- we use the Callaway and Sant'Anna (2021) estimator for the group-time average treatment effects (ATE), where groups are defined by different treatment timing
- we aggregate dynamically the ATE, obtaining event-study type plots

Overview of the results

After an automation spike, firm outcomes change:

- Employment, labour share, average wage, wage dispersion: $\uparrow$
- Outcomes evolution differs across size classes: diverging trends for micro/small firms and medium/large firms

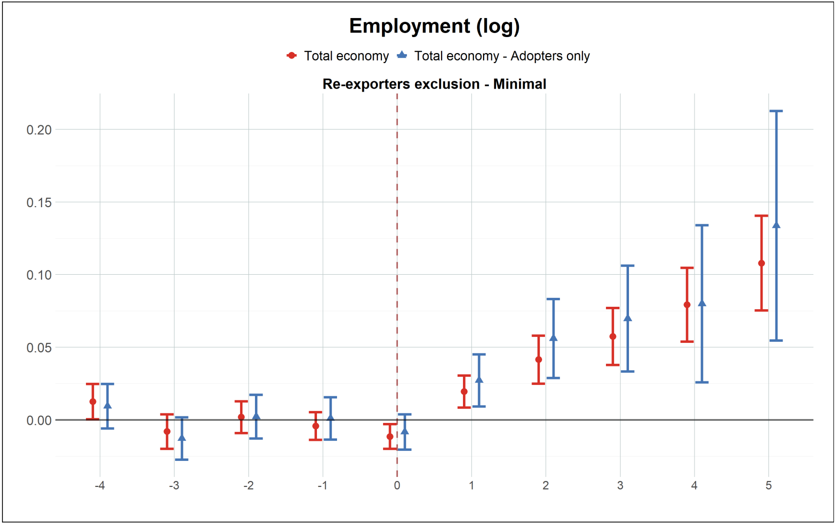
After an automation spike, workforce composition

- Small/no evidence of changes in broad occupational categories (blue/white collars and managers)
- Share of low-educated workers increases at the expense of highly educated workers

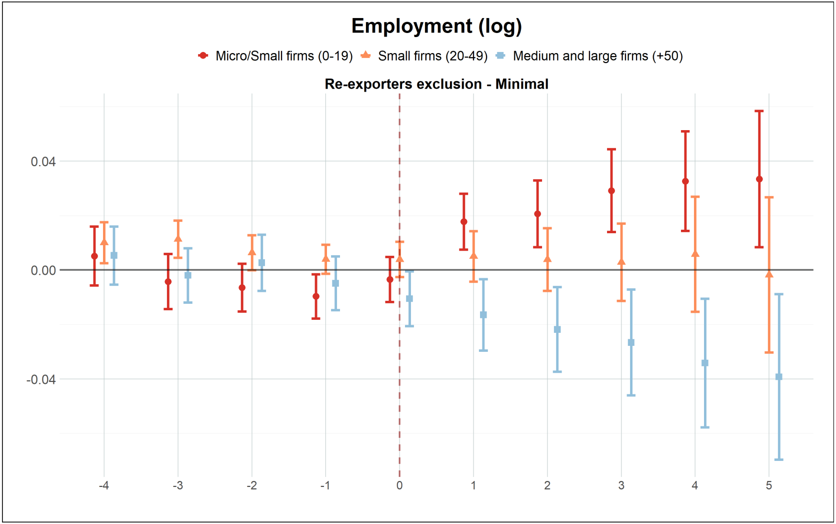
After an automation spike, contract types changes

- Small but significant descrease in temporary and part-time contracts

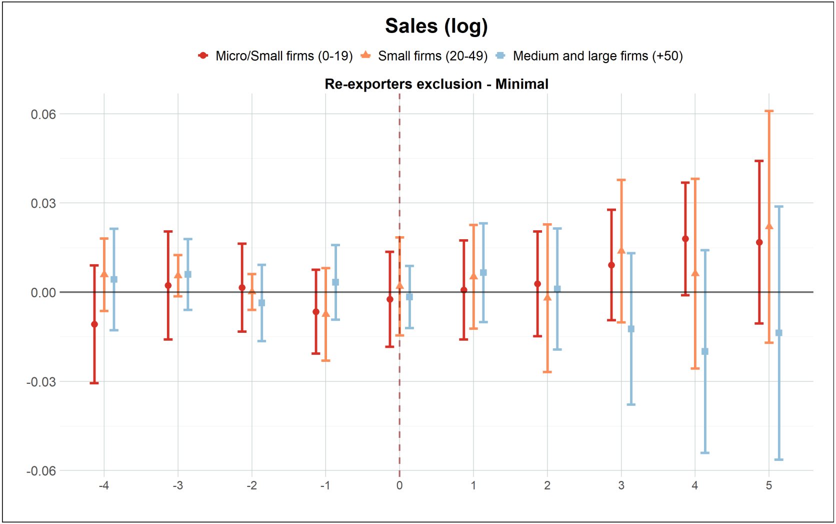
Employment


Employment (log)
Total economy
Total economy - Adopters only
Re-exporters exclusion - Minimal
0.20
0.15
0.10
0.05
0.00
-4
-3
-2
-1
0
1
2
3
4
5

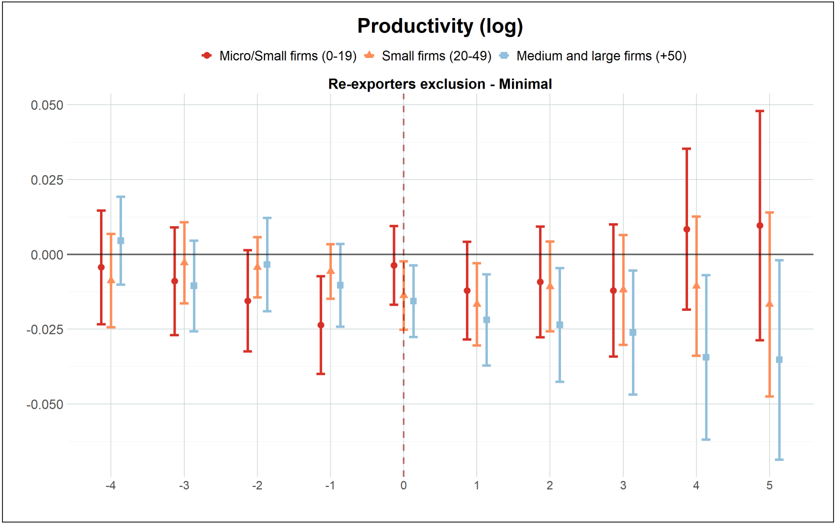
Employment - Size split



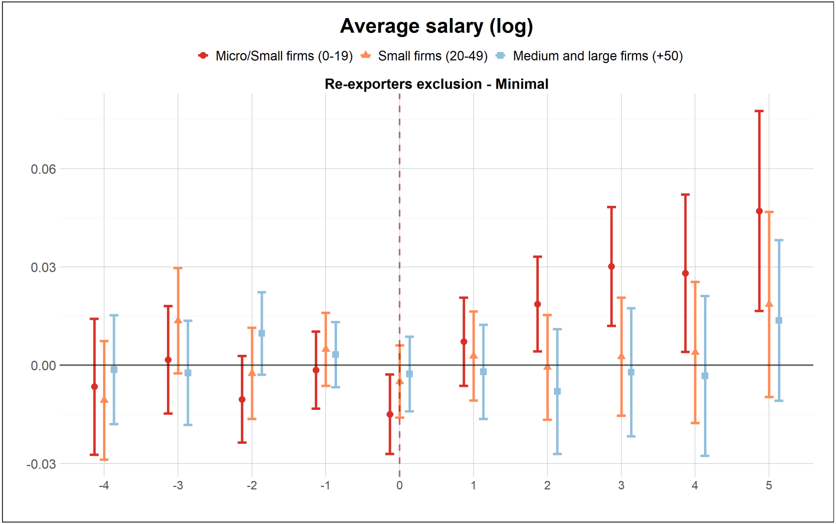
Sales


Sales (log)
Micro/Small firms (0-19)
Small firms (20-49)
Medium and large firms (+50)
Re-exporters exclusion - Minimal
0.06
0.03
0.00
-0.03
-0.06
-4
-3
-2
-1
0
1
2
3
4
5

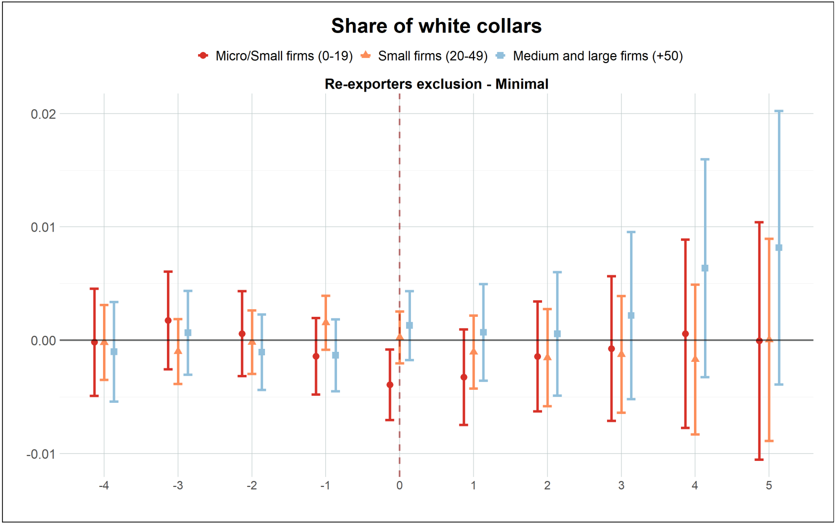
Productivity



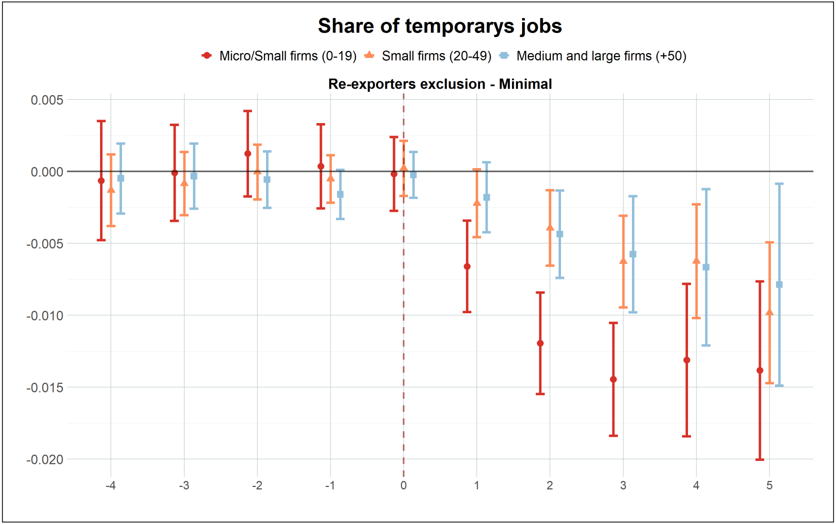
Average salary



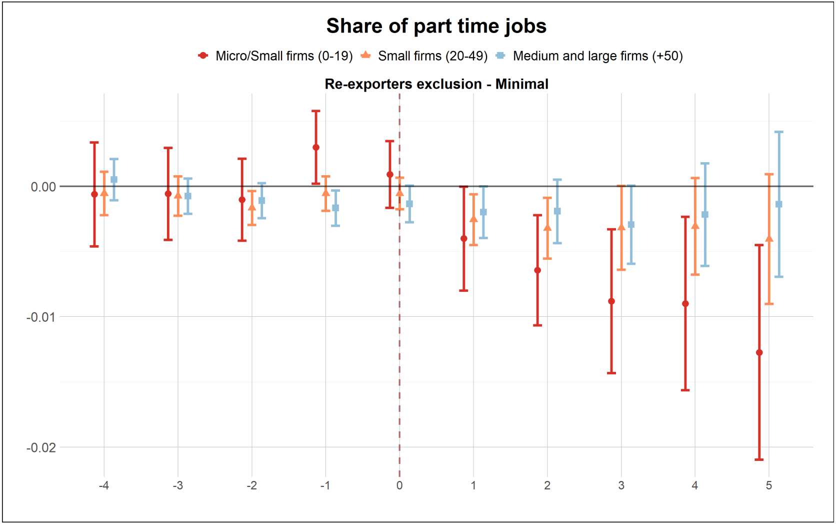
Occupational structure



Permanent contracts



Part-time jobs



Industry reallocation

	Total economy			Manufacturing		
	ΔEmp$_{15-19}$	ΔSales$_{15-19}$	ExPr$_{15-18}$ (Probit)	ΔEmp$_{15-19}$	ΔSales$_{15-19}$	ExPr$_{15-18}$ (Probit)
Prod. (log)	0.056 86***	0.065 44***	−0.205 83***	0.102 06***	0.105 05***	−0.2751***
	(0.003 46)	(0.005 81)	(0.005 57)	(0.004 93)	(0.009 03)	(0.0101)
Non Adopters	−0.53***	−0.344*	1.627***	−0.717***	−0.478**	2.189***
	(0.14)	(0.205)	(0.512)	(0.129)	(0.196)	(0.632)
Num.Obs.	975 856	975 856	1 108 913	453 397	453 397	501 725
Std.Err by	NC5	NC5	NC5	NC5	NC5	NC5
FE: Exporter	X	X	X	X	X	X
FE: Size Class	X	X	X	X	X	X
FE: NC5	X	X	X	X	X	X
FE: Region	X	X	X	X	X	X

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Linear model for the employment and sales in the span 2015-2019 at the firm-level compared with a probit model for the exit probability in the span 2015-2018. Explanatory variables include firm's labour productivity, 5-digits industry dummies, and a set of firm-level controls, and a dummy labelling non adopters.

Industry-level performance

	ΔEmp$_{15-19}$	ΔAER$_{15-19}$
ΔSales$_{15-19}$	0.7396***	0.866*
	(0.0551)	(0.460)
SpikeVal$_{11-19}$	−0.638**	−0.135
	(0.264)	(7.520)
Num.Obs.	6911	6718
R2 Adj.	0.656	0.187
Std.Err. by	NC2	NC2
FE: NC2	X	X

Linear model for cumulated employment growth (2015-2019) ΔEmp. Explanatory variables include a set of controls and a measures of automation adoption intensity for the sectors, SpikeVal$_{\mathbf{11-19}}$, i.e. the value of automation good imported through the spikes relative to the total import of the sector

Concluding remarks

- Results tend to confirm *benign* effects of automation within adopting firms yet highlighting high heterogeneity depending on the size class. Productivity and scale effects prevail over displacement effects for micro/small firms, displacement effect prevails for medium and large firms
- Workforce composition. Small or no evidence of changes in broad occupational categories. Increase of shares of older workers, low-educated workers
- Post-spike expansion is coupled with a positive effect on wage and labour share, but also on wage inequality
- Contract types. Small decrease in temporary and part-time contracts
- Evidence of intra-industry reallocation: adopting firms grow at the expense of non-adopting firms
- Aggregate effects: employment grows less in more automation-intensive sectors

Thank you!

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.

Return

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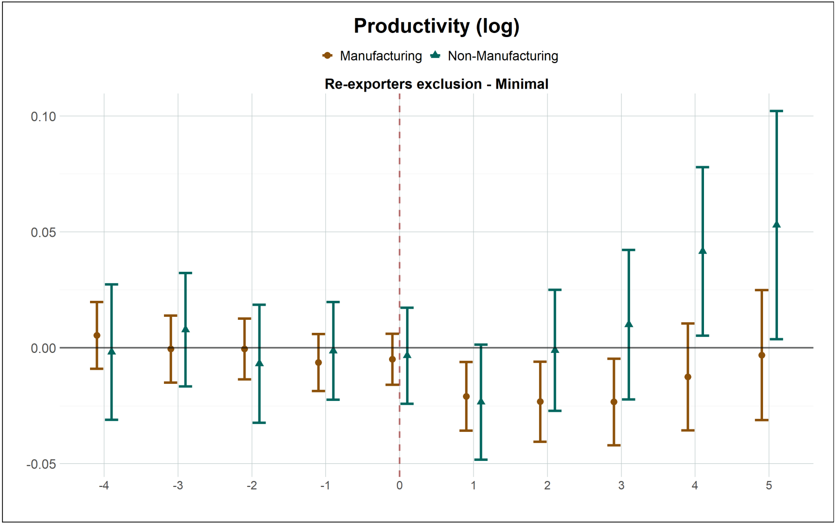
Productivity - Manufacturing vs Non-Manufacturing



Employment - Pavitt Taxonomy