Automation adoption and export performance: Evidence from French firms

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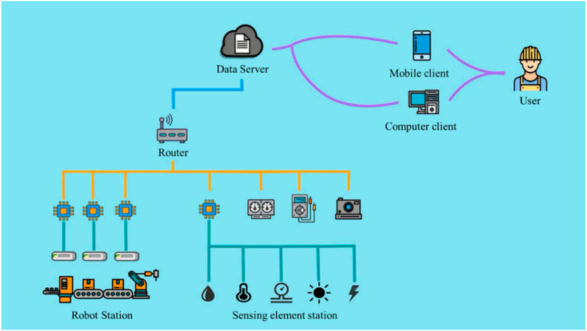
CITP seminar

Introduction

What is automation?

Automation is the application of technology, programs, robotics or processes to achieve outcomes with minimal human input.



Source: Lee et al., 2021

Motivation

Automation and the future of work

Previous literature

Automation increases firm performance

Automation adoption $\rightarrow$ Firm performance

- *Employment and wages*
  Studies on the firm level impact of automation generally show an increase in employment and wages
  (Acemoglu, Lelarge, and Restrepo, 2020; Dixon, Hong, and Wu, 2019; Domini et al., 2021, 2022; Humlum, 2021; Koch, Manuylov, and Smolka, 2021)

- *Market-stealing effect*
  Automation can then be viewed as a source of firm competitiveness leading to increases in market share
  (Bajgar et al., 2019; Acemoglu and Restrepo, 2020; Babiana et al., 2020; Firooz et al., 2022)

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Trade data can help identifying the sources of this competitiveness

This paper

Automation and trade

Automation affects trade patterns

- Robots can change the global organisation of production $\rightarrow$ reshoring (Artuc et al., 2019; Faber, 2020; Krenz et al., 2021)
- Robot adoption thus affects countries' specialisation and positioning in GVCs (Artuc et al., 2022)

Automation and (trade) shocks

- Automation can strengthen firms' resilience to shocks and disruptions, e.g. COVID-19 (Calza et al., 2023)

Automation and export performance

- Robot adoption increases firms' export start and survival, export sales and share (Alguacil et al., 2022, Spanish firms)

Mechanisms

Automation, product innovation and export performance

Automation adoption $\rightarrow$ Product portfolio $\rightarrow$ Export performance

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- Automation could play an important role to promote firms' exports performance through new products (product innovation) or lower costs (process innovation)

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- Automation could play an important role to promote firms' exports performance through new products (product innovation) or lower costs (process innovation)
  - Success in export markets with either existing or new products (Dollar, 1986; Jensen and Thursby, 1987; Lachenmaier and Wößmann, 2006)
  - Firms grow by adding products, but face uncertainty when doing so (Braguinsky et al., 2021)
  - Export growth at product level depends on how "core" to the firm they are (Bontadini et al., 2023)

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- Multi-product firms change the composition of their product portfolio in response to shocks in competition and demand (Mayer et al., 2014, 2021)

Mechanisms

Automation, product innovation and export performance

Automation adoption → Product portfolio → Export performance

Automation and product innovation - Positive channel

- Automation can improve firm capabilities and ability to upgrade their products (Szalavetz, 2019)
- Robots can improve efficiency (Acemoglu and Restrepo, 2019) and create customized products (Artuc et al., 2019; Faber, 2020; Krenz et al., 2021).
  - The introduction of **3D printing** boosted exports of producers of hearing aids (Freund et al., 2021, Weller et al., 2015)

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Automation and product innovation - Negative channel via allocation dilemma

- Negative association between robot adoption and the probability to introduce product innovations, except for large investments (Antonioli et al., 2024)

Mechanisms

Automation, product innovation and export performance

Automation adoption $\rightarrow$ **Export** portfolio $\rightarrow$ Export performance

Automation may change the content of the export portfolio

- embodied technology facilitates the exports of intermediate and capital goods (Rijesh, 2020, Indian firms)
- automation adopters produce more varieties, engage more in exports and imports (Ing and Zhang, 2022, Indonesian firms)

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Automation may change the quality of exported products

- Imported inputs, technologies and robot adoption in particular leads to increases in the quality of exported products, especially in developing countries (Castellani and Fassio, 2019, Swedish firms; DeStefano et al., 2021; Hong et al., 2022, Chinese firms; Navaretti et al., 2004)

Our contribution

We study whether and how automation adoption affects firms' export performance.

What:

- We consider a broad array of automation technologies
- We consider various export outcomes
- We explore heterogeneity across several dimensions

How:

- We exploit transaction-level customs data from France
- We execute a staggered diff-in-diff analysis, resorting to novel methodologies in the field (Callaway and Sant'Anna, 2021)

Data and variables

Data and variables

Datasets

- DGDDI: customs database
  - Import and export flows, trade value, country of origin/destination, and an 8-digit product code (transaction level)
  - Our main variables on the left- (export performance variables) and right-hand side (automation adoption) are based on DGDDI data
- FICUS/FARE: balance-sheet and revenue-account data
- DADS *Postes*: employer-employee database (social security forms) covering all French firms with employees

Measuring automation adoption

We use **imports** of capital goods embedding **automation** technologies

- ***Why?*** Lack of systematic firm-level info on adoption of automation technologies
  - Done by several studies (Dixon et al., 2020; Bonfiglioli et al., 2020; Acemoglu et al., 2020; Aghion et al., 2020; Domini et al., 2021; Domini et al., 2022)
  - Exceptions: survey data (NL, US)

- ***How?*** Identified via product codes List
  - We build on a taxonomy by Acemoglu and Restrepo (2018)

Characterising automation adoption

Imports of such goods display the typical **spiky behavior** of investment
(Asphjell et al., 2014; Grazzi et al., 2016)

- They are *rare across firms*
  In a given year, only around 14% of importing firms import automation-related products; over 2002-2017, less than half of them do it

- They are *rare within firms*
  Among firms that do import such goods, close to 30% do it only once; the frequency decreases smoothly with higher values

- A firm's *largest* event of import of such goods (in a year) accounts for a *very large share* (around 70%) of its total across years

Automation spike = a firm's largest automation adoption event

Sample construction

Sample includes firms which import at least once over 2002-2019

We currently restrict analysis to manufacturing

	Firm-year obs.	Unique firms
All firms	20,894,189	3,377,101
Importers	2,376,967	440,576
- of which, manufacturing	**620,160**	57,436
Importers of automation	537,562	48,835
- of which, manufacturing	**237,158**	19,056

For some of the regressions, we only keep exporting firms, further reducing the sample; and the estimation also requires at least 2 observations per firm.

Empirical analysis

Empirical approach

Event-study (treated vs. never treated)

- *Event* = automation spike
- *Control group* = importers who never automate

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Solution:

- Controls (# employees, sales, labor prod) and
- Conditions (same 2-digit sector- and commuting area)

Empirical approach
Event-study regression - methods

$$Y_{it} = \alpha_i + \sum_{k \neq -1; k_{min}}^{k_{max}} \beta_k D_{it+k} + \delta_t + \epsilon_{it}$$

- Y_{it}: dependent variable of interest (export performance)
  - (log) export value,
  - # exported products, # export destination countries,
  - avg value per product, avg unit price, exports/sales
- D_{it+k}: dummy for firm having automation spike k periods away
- α_i: firm fixed effects; δ_t: year fixed effects; ϵ_{it}: error term

We set $k_{min} = -5$ and $k_{max} = 10$

Empirical approach
New staggered diff-in-diff methods

Problem: TWFE may provide biased estimates of the Average Treatment effect on the Treated (ATT)

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Solution: New staggered diff-in-diff methods

(Borusyak et al., 2021; Callaway and Sant'Anna, 2021; de Chaisemartin and D'Haultfoeuille, 2020; Sun and Abraham, 2021)

We employ the method by Callaway-Sant'Anna (2021)

- It makes all comparisons relative to the last pre-treatment period for each cohort, then averages across cohorts
- It allows conditioning on covariates to fulfill the parallel trend assumption

Main results
Average Treatment Effect on the Treated (ATT)

Table 1: Main results

	prob. export	log exports	log #countries	log #products	log unit price	log avg. exports	exports/ sales
Automation	-0.006	0.149***	0.070***	0.018	0.027	0.132***	0.014***
	(0.005)	(0.032)	(0.014)	(0.016)	(0.026)	(0.032)	(0.003)
Nb of obs	525,125	306,856	308,412	308,412	306,856	306,856	302,042

Main results
Event study

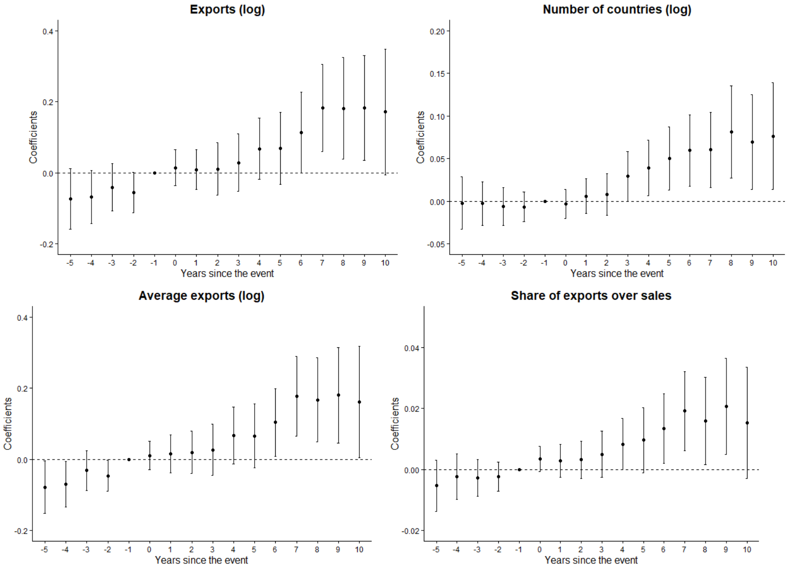

Figure 1: Various export outcomes around automation spikes (never treated, with controls,

Robustness check

Instrumental Variable analysis

Problem: endogeneity of the selection into automation

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Solution: exogenous variation in automation exposure:
(Bonfiglioli et al., 2024; Wang et al., 2024; Artuc et al., 2023)

- the current technological feasibility in the sector ("Prevalence"),
- how easily the tasks could be replaced in this firm given its original occupation structure ("Replaceability")
  (Autor and Dorn, 2013)
- the elderly proportion of the local labor force in a commuting zone (age in commuting zone "CZ_Age").
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Our instrumental variable, *Auto_Exposure*, is thus defined as follows:

$$\text{Auto\_Exposure}_{it} = \text{Prevalence}_{s-i,t} \times \text{Replaceability}_{i,2002} \times \text{CZ\_Age}_{c,2002}$$

where i, t, s, and c denote firm, year, sector, and commuting zone respectively.

Robustness check
Instrumental Variable analysis

Table 2: Automation adoption and exports: IV estimates.

	prob. export	log exports	log #countries	log #products	log unit price	log avg. exports	exports/ sales
Automation adoption							
Second stage	0.026	1.000***	0.176***	0.126**	0.409***	0.878***	0.132***
	(0.021)	(0.134)	(0.048)	(0.053)	(0.064)	(0.117)	(0.014)
First stage: Dependent variable is *Automation*							
Automation_exposure_i,t	0.006*	0.006*	0.006*	0.006*	0.006*	0.006*	0.006*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
F-statistic	452	452	452	452	452	452	452
Firm & Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	518,934	311,058	312,587	312,587	311,058	311,058	277,538

Notes: Standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Do firms' characteristics matter?
Innovation Status

Table 3: Characteristics of Firms - Innovation Status

	Log exports	# countries	# products	Log unit price	Log avg exports	Exports/Sales
Panel A1: Only innovating firms						
Automation event	0.151*	0.061**	-0.017	-0.002	0.168**	0.021**
	(0.054)	(0.026)	(0.027)	(0.048)	(0.055)	(0.007)
Observations	62,565	62,670	62,670	62,565	62,565	61,615
Panel A2: Only non-innovating firms						
Automation event	0.153***	0.068***	0.041**	0.060**	0.113**	0.012**
	(0.042)	(0.016)	(0.018)	(0.029)	(0.037)	(0.004)
Observations	244,291	245,742	245,742	244,291	244,291	240,427

Notes: Standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Resource allocation dilemma (Antonioli et al., 2024):

- Process innovation might be substituted with product innovation for innovating firms

Do firms' characteristics matter?
Productivity level

Table 4: Characteristics of firms - Productivity level

	Log exports	# countries	# products	Log unit price	Log avg exports	Exports/Sales
Panel B1: Only top productive firms						
Automation event	0.167**	0.067**	-0.020	-0.221***	0.184**	0.008
	(0.081)	(0.032)	(0.036)	(0.065)	(0.070)	(0.008)
Observations	191,045	192,169	192,169	191,045	191,045	188,295
Panel B2: Only bottom productive firms						
Automation event	-0.126	-0.010	0.034	-0.117	-0.159	0.005
	(0.126)	(0.052)	(0.061)	(0.135)	(0.121)	(0.016)
Observations	33,847	34,030	34,030	33,847	33,847	33,113

Notes: Standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Productivity threshold effect (Capello et al., 2022):

- High-productivity firms leverage automation effectively due to scale and resources.
- Low-productivity firms struggle with complementary investments and learning.

Restructuring of Global Value Chains?
Imports of non-automated products by origin

Table 5

	Non-automation imports (log)
Panel A: All firms	
Automation event	0.120***
	(0.030)
Observations	326,080
Panel B1: Only from EU countries	
Automation event	-0.179***
	(0.025)
Observations	229,388
Panel B2: Only from non-EU countries	
Automation event	0.149***
	(0.046)
Observations	218,564

Notes: Standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Substitution of imports from EU to non-EU:

- Substitution of tasks, change in input portfolio and expansion of production scale; no net reshoring
  (Stepleton and Webb, 2020; Artuc et al., 2022; Freund et al., 2022)

Conclusion

Discussion

- Export performance part of the positive effect of automation on firm performance
- Both intensive and extensive margins of exports improve compared to non-automators
- Automation leads to diversification; effect on composition of product portfolio still to be better defined
- Non-innovative and high productivity firms benefit the most
- Impact of automation on the import side: change in inputs needed or origin of inputs

Work in progress

- Role of product characteristics (core products, complexity of products)
- Role of types of automation technology

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

Return

Comparing automating to non-automating firms

T-tests

	No automation	Automation	T-test
Number of employees	20.44	**129.20**	***
Wage per hour (mean)	15.59	**17.30**	***
Log exports	11.38	**13.50**	***
Max share of exports	**0.78**	0.74	***
Number of export countries	4.26	**8.15**	***
Number of exported products	4.97	**9.72**	***
Log unit price	**1.33**	1.30	***

Return