Automation adoption and export performance: Evidence from French firms

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Automation and the future of work

Automation and firm performance

Automation adoption → Firm performance

- *Employment and wages*
  Studies on the firm level impact of automation show a positive effect on employment and wages
  (Acemoglu, Lelarge, and Restrepo, 2020; Dixon, Hong, and Wu, 2019; Domini et al., 2021; Humlum, 2021; Koch, Manuylov, 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; Auto et al., 2020; Babiana et al., 2020; Firooz et al., 2022)

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Can we identify more precisely the source of this competitiveness using trade data?

Automation and trade

Automation affects trade patterns

- Robots can change the global organisation of production
  → produce products at the home country rather than offshoring
  → reshoring (Artuc et al., 2019; Faber, 2020; Krenz et al., 2021)
- Automation 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, ex: COVID-19 (Bas et al., 2022)

Mechanisms: Automation, product innovation and export performance

Automation adoption → **Product portfolio** → **Export** performance

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Conceptual framework

- Firms adopt automation to increase their competitiveness
- 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)
- Indeed:
  - 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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  - Export growth at product level depends on how "core" to the firm they are (Bontadini et al., 2023)
- However, 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). For example, the introduction of **3D printing** boosted exports of producers of hearing aids (Freund et al., 2021, Weller et al., 2015)

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., 2022)

Mechanisms: Automation, product innovation and export performance

Automation adoption → **Export** portfolio → Export performance

Automation may change the content of the export portfolio

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

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 & Fassio, 2019, Swedish firms; DeStefano et al., 2021; Hong et al., 2022, Chinese firms; Navaretti et al., 2004)

Empirical evidence on automation and export performance

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

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

This paper

Our contribution

- We consider a broad array of automation technologies
- We consider various dimensions of export performance (value, country and product diversification, quality, price,)
- We investigate the underlying channels

Features

- 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; Borusyak et al., 2022)

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)
- FICUS/FARE: balance-sheet and revenue-account data
- DADS *Postes*: employer-employee database (social security forms) covering all French firms with employees

Main variables:

- Export value, number of exported products, number of export countries
- Firm-level events (spikes) of investment in automation (based on imports of relevant technologies)

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 appendix
  - 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 (robot) spike = a firm's largest automation (robot) adoption event

Measuring export performance

- Log export
- Number of exported products
- Number of exported countries

Identifying the channels

Change in product (export) portfolio

- number of new products (added to firm portfolio)
  - a product which was not sold before appears in the firm's exports
- Core vs. non-core products
  - Core product has the highest share in firms' exports; Other products are "non-core"

Change in product quality

- measuring product quality using theory-reliant approach (Khandelwal, 2010) ▸ appendix
- measuring price (adjusted and unit price)

Sample construction

Sample includes firms which import at least once over 2002-2017

We initially restrict analysis to manufacturing, but may expand to other sectors at a later stage

	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	563,531	43,405
- of which, manufacturing	242,504	19,267

Empirical analysis
(preliminary results!)

Empirical approach

Event-study within adopters of automation/AI
(treated vs. not yet treated) (Bessen et al, 2020; Domini et al, 2022)

- Accounts for spiky behavior
- Accounts for selection into automation/AI: only firms importing at least once automation/AI) ▸ Stats ▸ Regression
- Exploits heterogeneity in timing of the event among relatively similar firms
- Using a range of estimators to obtain robust results: TWFE, and staggered diff-in-diff

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Focussing on a battery of outcome variables:

- Export performance: Export, Nb of exported products, Nb of exported countries
- Heterogeneity analysis: Core vs. non core products; high vs. low income country destinations
- Identifying the channels: product quality; new products

Empirical approach
Assumptions

Two identification assumptions for diff-in-diff framework:

1. Parallel trends in the absence of treatment
   - We will show it is not credible when using never-treated observations, but it is when using not-yet treated ones
2. No anticipation: future treatment does not affect current outcomes
   - Firms may anticipate their decision and this might affect other decisions they make (Bessen et al. 2022) $\rightarrow$ care with causal interpretations

Empirical approach
New staggered diff-in-diff methods

A sprawling recent literature has shown that, in complicated designs with multiple groups and periods, and variation in treatment timing, TWFE may provide biased estimates of the ATT

→ 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 two of these new estimators:

- Callaway-Sant'Anna makes all comparisons relative to the last pre-treatment period for each cohort, then averages across cohorts
- Borusyak et al. regresses outcome on group and time FE in sample of untreated observations, to predict ("impute") the counterfactual for the treated

Event-study regression - methods

In sample of firms importing automation at least once, run the following dynamic Two-Way Fixed Effects (TWFE) specification:

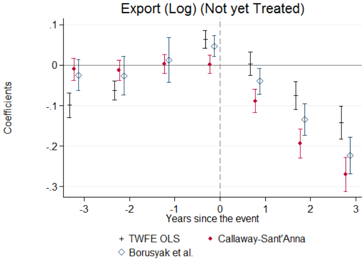
$$Y_{it} = \alpha_i + \sum_{k \neq -1; k_{min}}^{k_{max}} \beta_k D_{it+k} + \delta_t + \epsilon_{it}$$

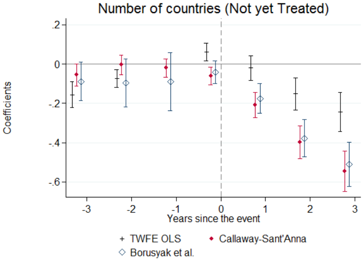
- Y_{it}: dependent variable of interest
- D_{it+k}: dummy for firm having automation spike k periods away
- α_i: firm fixed effects
- δ_t: year effects
- ϵ_{it}: error term

We set $k_{min} = -4$ and $k_{max} = 4$

Event-study regression - results

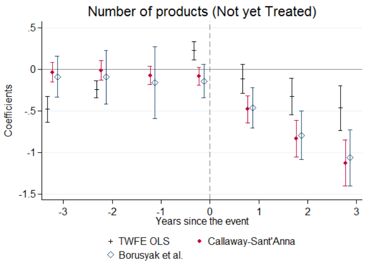
Export performance

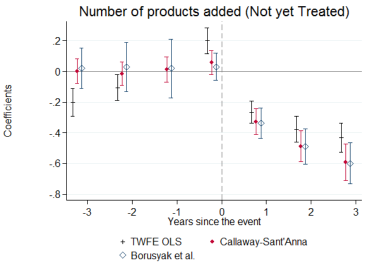




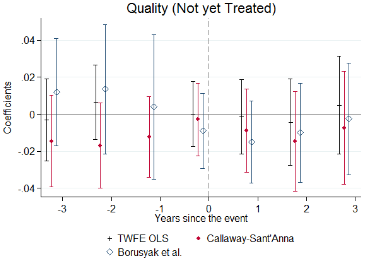
Event-study regression - results

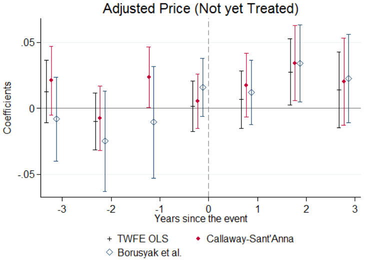
Testing the channels: Product innovation - Number of products and products added





Event-study regression - results
Testing the channels: Product quality and price



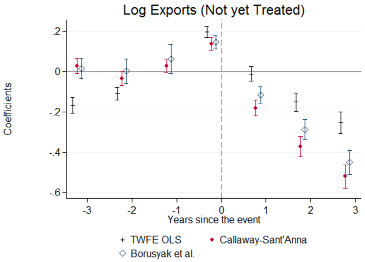


Event-study regression - results
Heterogeneity analysis

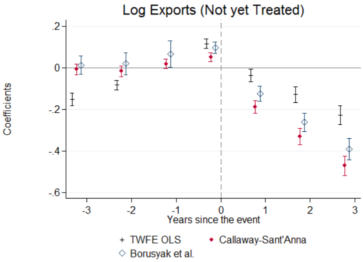
What explains the decrease in export sales and number of products?
Are all products impacted in the same way?

Event-study regression
Heterogeneity analysis

Core products



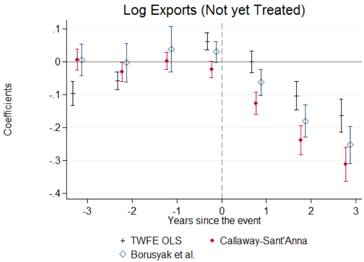
Non-core products



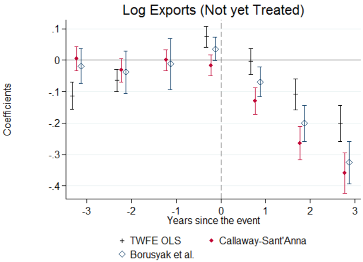
Sample: whole sample - automation spikes

Event-study regression - results
Heterogeneity analysis

High-income destinations



Low-income destinations



Sample: whole sample - automation spikes

Discussion and Next steps

Discussion

- Selection leads larger firms to more adoption.
- Caution against firm-level explorations using OLS or event study strategies to uncover the effects of advanced technology adoption (Acemoglu et al., 2023)
- Using staggered dif-in-dif methods within the group of adopting firms, we find that export sales decrease due to a reduction in the number of (new) products

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Next steps

- Understand better the innovation behaviour of firms adopting automated intermediate goods

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Next steps

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Feedback is very welcome

Thank you for your attention!

Data appendix

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

Appendix: measuring quality

We use a **theory-reliant approach** (Khandelwal et al., 2013)

- Run the OLS regression:

$$\ln q_{fpct} + \sigma \ln p_{fpct} = \alpha_p + \alpha_{ct} + \epsilon_{fpct}$$

  α_{ct}: country-time fixed effect
  α_p: product fixed effect
  $\ln q_{fpct}$: log quantity of firm f - product p - country c - time t
  $\ln p_{fpct}$: log unit price
  σ: elasticity of substitution of a product

- Use the values of σ estimated by Broda and Weinstein (2004); if not available then σ=4 (Khandelwal et al., 2013; Simonowska and Waugh, 2014; Giri et al., 2021)

- Estimated quality:

$$\ln \hat{\lambda} = \frac{\hat{\epsilon_{fpct}}}{\sigma - 1}$$

- Quality-adjusted price:

$$\ln p_{fpct} - \ln \hat{\lambda_{fpct}}$$

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**	***
Quality	1.95	**2.04**	***
Quality adjusted price	**1.22**	1.05	***
Log unit price	**1.33**	1.30	***

Return

Comparing automating to non-automating firms
OLS regression

In sample of firms importing at least once, run the following:

$$\Delta Y_{it} = \beta A_i + \gamma X_i + \delta_t + \epsilon_{it}$$

- Y_{it}: dependent variable of interest (e.g. log export value)
- A_i: dummy for the firm adopting automation over the 2002-2017 period
- X_j: additional controls (incl. sector dummies)
- δ_t: year effects
- ϵ_{it}: error term

SEs clustered at the firm level
β indicates whether automating firms show different trends in the variables of interest Return

Comparing automating to non-automating firms
OLS regression results

D.V.: Δ in	Export (Log)	Number countries	Number products	Quality	Quality-adj. price	Unit price
A	0.031***	0.041***	0.172***	0.001	-0.005*	-0.004*
	(0.003)	(0.006)	(0.018)	(0.003)	(0.003)	(0.002)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Sector effects	Yes	Yes	Yes	Yes	Yes	Yes
N	284,590	287,598	287,598	230,878	167,838	226,617
R^2	0.006	0.003	0.005	0.003	0.015	0.007

Automating and non-automating firms are on different trends

This would violate the parallel trends assumption, crucial for identification in diff-in-diff designs

Return

Comparing different cohorts of automating firms

Are not-yet treated observations a good counterfactual?
In sample of observations between 3 and 1 years before a spike, run the following:

$$\Delta Y_{it} = \beta C_i + \gamma X_i + \delta_t + \epsilon_{it}$$

- C_i: cohort dummies (spike year)

SEs clustered at the firm level

D.V.: Δ in	Export (Log)	Number countries	Number products	Quality	Quality-adj. price	Unit price
F on C_i	1.00	0.85	1.38	1.23	1.16	0.76
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Sector effects	Yes	Yes	Yes	Yes	Yes	Yes
N	38,457	27,610	27,610	23,618	23,618	23,618
R^2	0.001	0.006	0.010	0.007	0.019	0.005

Return