Automation Adoption and Export Performance: Evidence from French Firms

Thao Trang Nguyen[1], Giacomo Domini[2], Marco Grazzi[3], Daniele Moschella[4], and Tania Treibich[5,4]

[1]UNU-MERIT - Maastricht University (The Netherlands)
[2]Utrecht University School of Economics (The Netherlands)
[3]Department of Economic Policy, Università Cattolica del Sacro Cuore, Milano (Italy)
[4]Institute of Economics & Department EMbeDS, Scuola Superiore Sant'Anna, Pisa, (Italy)
[5]School of Business and Economics, University of Maastricht (The Netherlands); Science-Po Paris, OFCE-DRIC, Sophia Antipolics (France)

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1 Introduction

The debate about the impact of new automation technologies (the so-called Fourth Industrial Revolution, 4IR) has mainly focused on their impact on employment, i.e. whether they will replace labor, and which employees may be most at risk (Frey and Osborne, 2017; Nedelkoska and Quintini, 2018; Acemoglu and Restrepo, 2020; De Vries et al., 2020). However, this debate seems to ignore the contributions of new automation technologies to the export activity of firms and countries (Alguacil et al., 2022), and the global organization of production in general. These technologies offer the flexibility to create customized products (for example to adjust to preferences in different markets), increase the quality of products by reducing production errors and increasing the accuracy of technical processes (DeStefano and Timmis, 2021; Lin et al., 2022) or more generally, may change the way firms source their inputs and organize their production across countries. Indeed, it may now be more cost-effective to reshore production (using automated processes), rather than keeping labor-intensive tasks in low-wage countries (Faber, 2020; Krenz et al., 2021).

Though informative, the above-mentioned research mostly considers the effect of robot adoption on export performance, and ignores other automation (4IR) technologies , for example 3D printers, automatic machine tools, etc. In addition, they focus on overall quality and export performance, and do not discuss how these relate to changes in firms' export portfolio.

In this paper, we use extensive import and export data from France to fill these gaps. Our analysis focuses on automation adoption that affects export performance and productivity. We use French firm-level data from the period 2002–2019 and examine how automation technologies affect various dimensions of firms' export activity, namely value, product and country diversification, quality, and price. To address selection into automation adoption, we implement a staggered difference-in-difference analysis on a sample of adopting firms only, resorting to novel methodologies in the field (Callaway and Sant'Anna, 2021). We find that after the automation event, firms decrease their exports value, number of exported products, and number of exported countries. We find heterogeneity by technology, as no changes in export performance are detected for robots; across industries, as results are driven by mechanical industries; and by firm size, as small firms appear more negatively affected.

Our work contributes to two strands of literature. First, we contribute to the literature on the sources of export (quality) performance of exporting firms. Lin et al. (2022) study the quality upgrading effect of robots, this time in a sample of Chinese firms. They also find that robot adoption promotes quality upgrading of Chinese firms, driven by an increase in labour productivity and human capital level. Alguacil et al. (2022) analyse instead the effect of robot adoption on general export performance in a sample of Spanish manufacturing firms from 1990–2014. They find that robot adopters increase their export probability, export sales and share of exports in total output. They argue that this result is explained by the increase in total factor productivity, product innovation, and imports.

Second, this paper also contributes to the literature on the firm-level effects of automation, and the benefits and challenges of adopting such technologies. Previous studies have included a large range of outcome variables such as the decision to export, export variety (Alguacil et al., 2022), reshoring (Krenz et al., 2021), or employment (Domini et al., 2021) and wages (Domini et al., 2022). However, previous literature only considers specific and/or older technologies, for example, DeStefano et al. (2018) and DeStefano et al. (2022) focus on ICT and broadband use, Alguacil et al. (2022) and Lin et al. (2022) on robot adoption, Yang (2022) and Corrado et al. (2021) on artificial intelligence. We, on the other hand, consider a broad set of 4IR automation technologies (Culot et al., 2020).

The rest of the paper is organized as follows. Section 2 describes our data and our automation measure. Section 3 discusses our empirical strategy. Section 4 reports our results. Section 5 concludes our paper.

2 Data

2.1 Sources

For our analysis, we match data from several French administrative datasets. The main source is the transaction-level customs data compiled by the French customs office (*Direction Générale des Douanes et des Droits Indirects*, DGDDI), from which we compute our main left- and right-hand side variables, as explained later in this section. This contains detailed information on each import or export transaction involving a French firm, notably value, country of origin/destination, and product code. The latter is available at the 8-digit level of the European Union's Combined Nomenclature, which for the first 6 digits corresponds to the international Harmonized System (HS) classification. Further details about this dataset can be found in the paper by Bergounhon et al. (2018).

We extract additional information from other databases provided by the French national statistical office (*Institut national de la statistique et des études économiques*, INSEE). The first is DADS *Postes*, an employer-employee dataset based on the mandatory forms that all establishments have to submit to the social security authorities regarding their employees. We use this dataset to retrieve variables related to employment, such as wages and number of employees, as well as a firm's sector. As in Domini et al. (2021), we assign each firm a permanent 2-digit sector based on the most frequent sector code across years. Finally, we use FICUS and FARE, two datasets (with the latter being the successor of the former from 2009 onwards) based on the fiscal statements that French firms must submit to the tax authorities, to retrive balance-sheet and revenue-account variables, such as value added.

2.2 Variables

2.2.1 Measures of export performance

We use the DGDDI data to compute a battery of variables that reflect different dimensions of a firm's export activity, namely total export value, number of export countries, number of exported products (at the 8-digit HS level), average unit price, quality and quality-adjusted price of exported products. The last two are based on the approach developed by Khandelwal (2010), based on the intuition that, conditional on price, higher quality products have higher market share, which is largely applied in the literature (DeStefano and Timmis, 2021; Lin et al., 2022). Khandelwal et al. (2013) apply this approach to the firm-product level, running the following OLS regression on the exports of Chinese textile and clothing firms:

$$\ln q_{fhct} + \sigma \ln p_{fhct} = \alpha_h + \alpha_{ct} + \epsilon_{fhct}$$

where $\ln q_{fhct}$ is the log quantity of the exports by firm f of product h to country c at time t, $\ln p_{fhct}$ is the corresponding log unit price, α_{ct} is a country-time effect , α_h is a product fixed effect , and σ is the elasticity of substitution of a product. We use the σ estimated by Broda and Weinstein (2006) and, for products for which these authors do not provide σ, we set $\sigma = 4$ as in Khandelwal et al. (2013).

After running the equation above, (log) quality can be estimated as:

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

and (log) quality-adjusted price as

$$\ln p_{fhct} - \ln \hat{\lambda_{fhct}}.$$

2.2.2 Measure of automation adoption

Our measure of firm-level adoption of automation technologies is also based on customs data, in particular on the imports of capital goods embedding automation technologies. Using import data to capture firm-level adoption of robots and other automation technologies is a popular solution among empirical studies on the topic (Dixon et al., 2019; Bonfiglioli et al., 2020; Acemoglu et al., 2020; Domini et al., 2021, 2022), in the absence of systematic administrative data on the adoption of these technologies, which only recently have started being collected by some national statistical offices, notably in the Netherlands (Bessen et al. 2020, 2023) and the United States (Zolas et al., 2021).

We employ the same procedure as in Domini et al. (2021), namely we identify 6-digit HS product codes related to automation technologies based on a taxonomy developed by Acemoglu and Restrepo (2020), to which we add a code for 3D printers as identified by Abeliansky et al. (2020). In this way, we cover a broad array of automation technologies, including industrial robots, dedicated machinery, automatic machine tools, automatic welding machines, automatic textile machines (including for weaving and knitting), automatic conveyors and regulating instruments, plus 3D printers. See Domini et al. (2021, 2022) for details, including product codes, and a discussion of potential limitations.

2.3 Samples: definitions and descriptive statistics

As we use import data to construct our measure of automation adoption, we restrict the scope of our analysis to importing firms, which are likely to source their inputs on international markets. These are defined as firms that import at least one year over the period 2002-2019. They represent around 12% of French firms, but account for more than half of total employment (see Domini et al. 2022, Table 1). For our analysis, we further restrict the focus to manufacturing firms. Furthermore, as will be explained below, we will run our main exercise on a sample of firms that import automation technologies at least once over the period 2002-2019, henceforth referred to as "adopters". Table 1 shows the number of observations and unique firms in each sample. Table 2 compares the means of selected variables for adopters and non-adopters, where the latter are firms in our sample of importing firms that never import goods embedding automation technologies. Adopters employ more people and pay higher hourly wages to their employees. In terms of export performance, they have higher export values, larger numbers of export countries and exported products, although the maximum share of exports is lower. They also have higher quality compared to non-adopters, and lower (quality-adjusted) unit price.

Table 1: Sample composition, 2002-2019.

	Firm-year obs.	Unique firms
All firms	20,894,189	3.377.701
Importers	2,376,967	440,576
- of which, manufacturing	620,160	57,436
Importers of automation (adopters)	563,531	43,405
- of which, manufacturing	242,504	19,267

Source: our elaborations on DADS and DGDDI data.

Table 2: Comparing automating and non-automating firms: Means of selected variables.

	Non-automating	Automating	T-test
Number of employees	11.38	**13.50**	***
Wage per hour (Mean)	15.59	**17.30**	***
Log exports	11.38	**13.50**	***
Max share of exports	**0.78**	0.74	*
Log top value	4.26	**8.15**	***
Nb export countries	4.26	**8.15**	***
Nb 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	***

Source: our elaborations on DADS and DGDDI data. Sample: Importing firms in manufacturing. Note: *, **, and *** denote $p < 0.10$, $p < 0.05$ and $p < 0.01$, respectively.

3 Empirical Strategy

As our automation spike variable represent single, major events for each firm we observe, an event-study design is suitable to investigate what happens to a firm's export performance around such an event. The classic two-way fixed-effects (TWFE) event-study specification reads as follows:

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

where Y_{it} is the dependent variable of interest, D_{it+k} is a dummy denoting whether a firm has an automation spike k periods away, α_i is a firm fixed effect, δ_t is a year effect, and ϵ_{it} is the error term. Coefficient β_k refers to the effect of automation k years after a spike (or before if $k < 0$), relative to the baseline year ($k = -1$), whose coefficient is omitted (Freyaldenhoven et al., 2021). We set $k_{min} = -4$ and $k_{max} = 6$, meaning that β_{-4} (β_6) refers to the average outcomes four (six) or more years prior to (after) the automation event.

For a causal interpretation of the estimated coefficients $\hat{\beta}_k$, two assumptions need to be satisfied: first, the parallel trends assumption (PTA), stating that treated and untreated units should follow the same trend in the absence of treatment; second, no anticipation, meaning that outcomes do not depend on future treatment. Furthermore, a recent strand of literature has shown that, in complicated designs with multiple time periods and variation in treatment timing, the TWFE estimator may provide an inconsistent estimate of the causal effect. In the rest of this section, we discuss these issues.

First, the PTA requires a careful choice of the control group. In the previous section, Table 2 showed that there are substantial differences between firms that at some point import capital goods embedding automation technologies ("adopters") and those that do not ("non-adopters"). In a TWFE regression, such level differences are controlled for by the fixed effects. However, it is reasonable to expect that adopters and non-adopters may also be on different trends. Following Bessen et al. (2023), we investigate this by means of the following OLS regression:

$$\Delta Y_{it} = \beta A_i + \gamma X_i + \delta_t + \epsilon_{it} \tag{2}$$

where Y_{it} is one of the outcome variables of interest, A_i is a dummy denoting that a firm adopts automation over the 2002-2019 period, δ_t is year effect, and X_i are additional controls for firm-level characteristics including sector dummies,and ϵ_{it} is the error term. The coefficient of interest is β, which tells us whether automating firms show different trends in the outcome variables. The results from this exercise, not shown here in the in the interest of space, reveal significantly different trends, implying that choosing non-adopters as a control group would not satisfy the PTA. Hence, as in Bessen et al. (2023), we will run our event study regression only on the sample of firms that, at some point, adopt automation, exploiting differences in treatment timing for identification.

As for the no-anticipation assumption, Bessen et al. (2023, p. 16) point out that it may be difficult to maintain at the firm level, "because firms that decide to automate are more able to anticipate their own decision and this might affect other decisions they make in anticipation of the automation event." In general, we will use caution in making causal claims, and rather interpret our results as descriptive when more appropriate.

Finally, a TWFE regression may fail to return correct estimates of causal effects in designs with more than two time periods where treatment is staggered and there is variation in treatment timing, i.e. units can be treated in different point in times, resulting in multiple treatment groups at different times (Roth et al., 2022). In such designs, the classical TWFE estimator will will be biased due to negative weights on the average treatment effects for certain groups and time periods, as explained in several recent studies (Goodman-Bacon, 2021; Roth et al., 2022). To address this concern, several approaches have been proposed by a sprawling stream of literature (Borusyak et al., 2021; Goodman-Bacon, 2021; Sun and Abraham, 2021; Callaway and Sant'Anna, 2021; De Chaisemartin and d'Haultfoeuille, 2020).

In this study, we will make use of the estimator by Callaway and Sant'Anna (2021), which is calculated by making all comparisons relative to the last pre-treatment period for each cohort (i.e. the group of firms treated at a certain period), then averaging across cohorts.

4 Results

Figure 1 reports the results from our event study on automating firms only. After an automation spike, firms turn out to first slightly increase their export value in the spike year, then reduce it. A regression with a dummy for whether a firm exports in a certain year or not (top-right) reveals that the extensive margin is impacted modestly if at all: the probability is 1 percentage point lower three years after a spike, compared to the pre-spike period. Hence, what drives our result on the export value seems to be the intensive margin, rather than the extensive one. The number of export countries and of exported products also decreases: firms thus become more specialised. No significant change is detected for quality; while a slight, barely significant increase in quality-adjusted price appears two years after an event. Notice that, with the exception of the regression with the dummy variable as dependent variable, no significant pre-trends appear. These results are qualitatively confirmed if a balanced sample is employed (not shown here), although the magnitude of the coefficients is smaller.

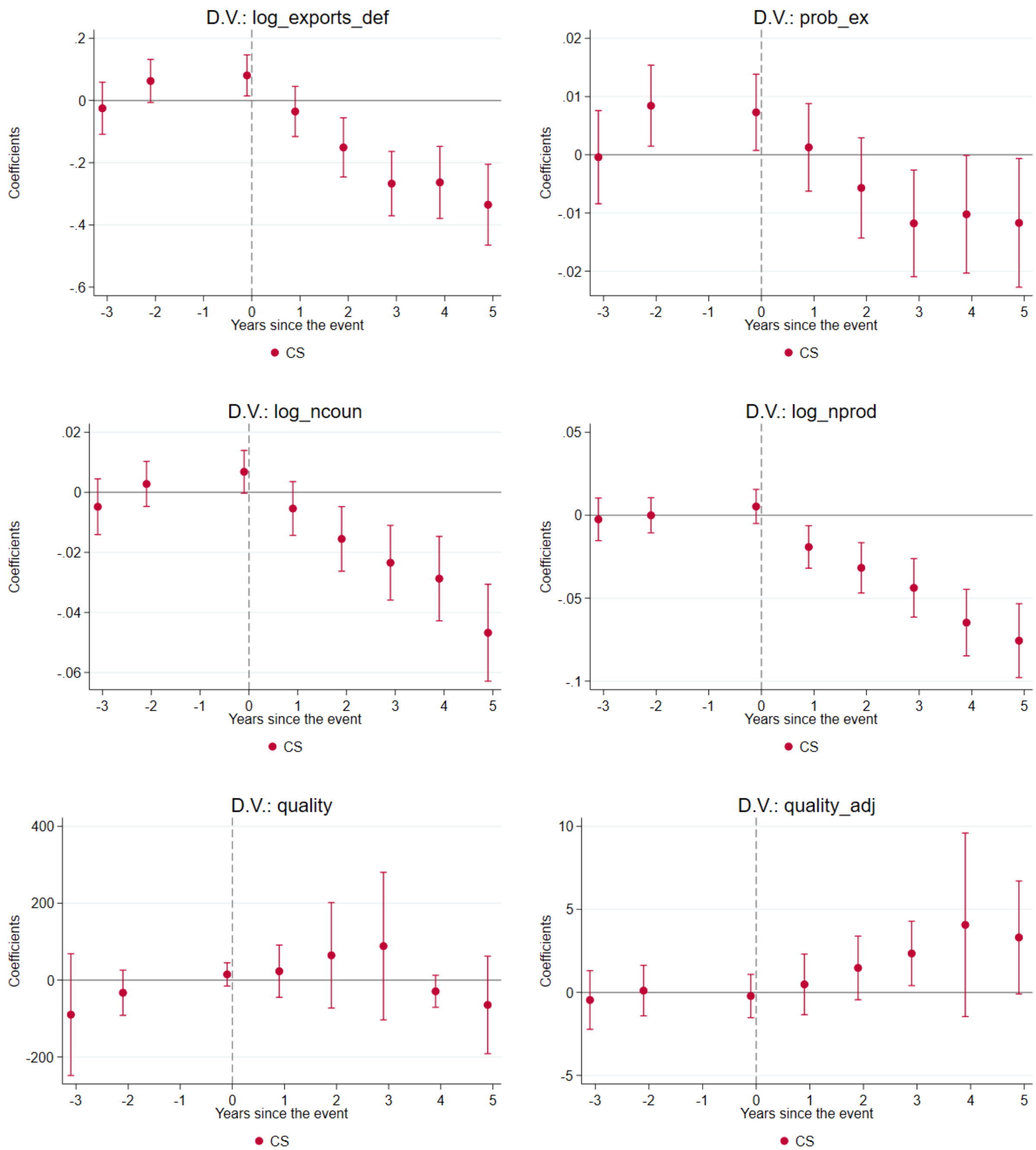


Figure 1: Various export outcomes: Main estimates.

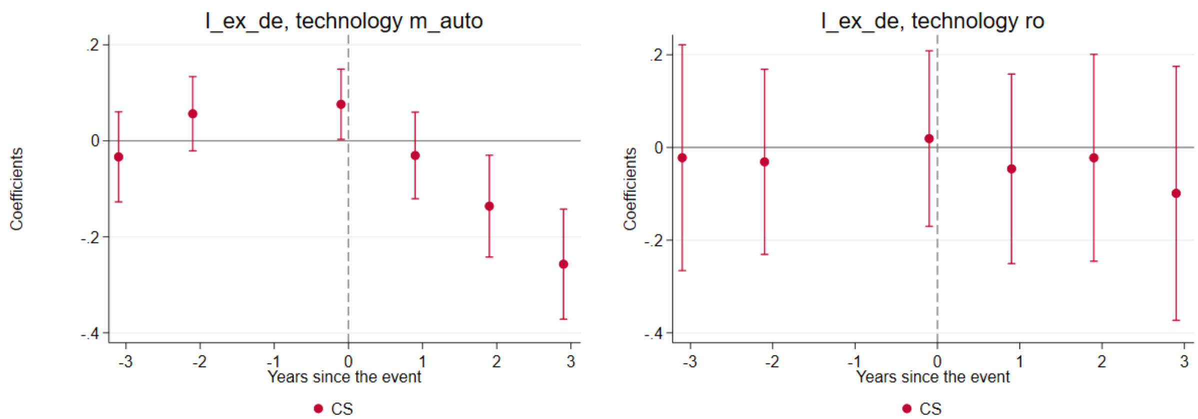
Heterogeneity analyses

The results just shown may be driven by some specific products, destinations, technologies, and types of firms. We conduct several heterogeneity analyses, to investigate whether and how results differ between core and non-core products - where a firm's core product is that with the highest share in its exports -, between high-income and low-income destination countries, between patenting and non-patenting firms, and across different automation technologies, firm size classes, and industries.

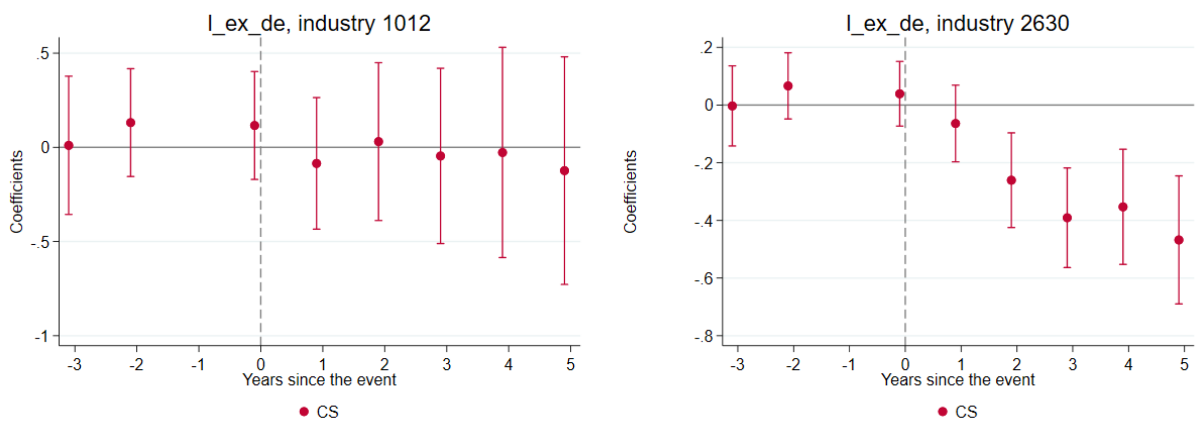
Only the last three of these dimensions revealed remarkable differences. Results referring to them are shown in Figure 2. First, we observe negative coefficients in line with the main estimates as per the previous figure for automatic machine tools, but not for robots: after a spike of investment in robots, no change in export value is detected. Furthermore, when we look across industries, we observe no impact of automation in food, beverage and tobacco (shown in the figure; but also in other industries such as chemicals and non-metallic minerals), while coefficients are similar to the main estimates in mechanical industries. The heterogeneity across technologies shown above suggests that industry differences may depend on which specific technologies are more prevalent in each industry.

Another heterogeneity dimension is firm size. Firms investing in automation technologies have to pay a fixed cost - which can be difficult for some firms (Koch et al., 2021), especially small ones. Therefore, the effect of automation adoption on export performance may vary and depend on firm size. Indeed, we find this effect looks larger fir small firms, not by larger medium firms which aligns with the argument that small firms meet challenges when dealing with the cost of automation adoption.

(A) Left: Automatic machine tools; Right: Robots



(B) Left: food, beverage and tobacco industry (ISIC Rev. 4 10-12); Right: mechanics and electronics (ISIC Rev. 4 26-30)



(C) Left: small firms (10-49 emp.); Right: medium firms (50-249 emp.)

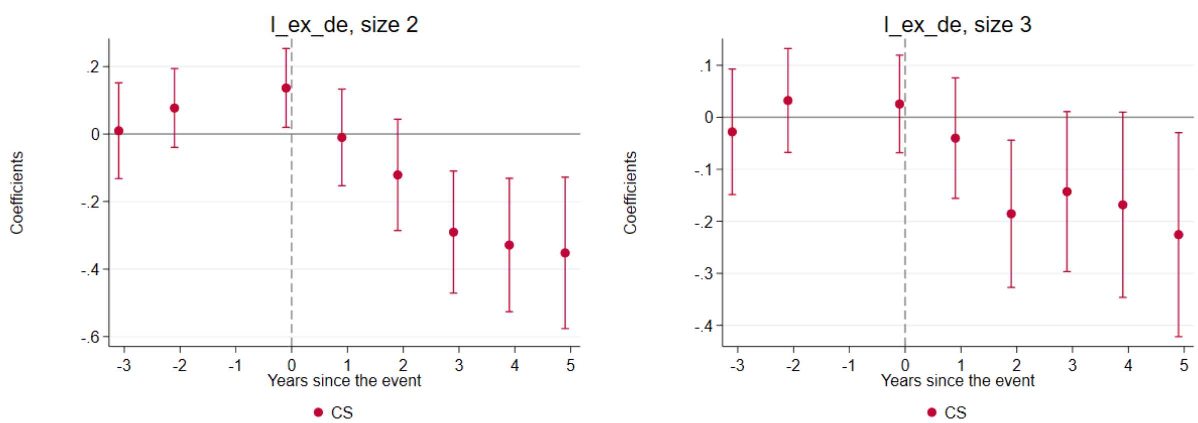


Figure 2: Export value: Heterogeneity technologies, industries, and firm size classes.

5 Conclusion

While the debate around the impact of new automation technologies on job displacement and reshoring has been intense, it tends to overlook the potential benefits of these technologies on firms' export activity. Previous research has shown that robot adoption can improve export quality and increase the probability, sales, and share of exports. However, these studies have focused mainly on robot adoption and have not considered other automation technologies or product dimensions. This paper aims to fill these gaps by examining how automation technologies affect firms' export activity using French firm-level data from 2002 to 2019. We find that, while automating firms are on steeper growth trends in terms of exports value, number of exported products, and number of export countries, when comparing with non-automation firms. However, after an automation spike, these variables decrease, hence trends tend to flatten. These results do not hold for robot adoption spikes, pointing to heterogeneous effects across types of automation technologies. Significant heterogeneity across firms is also unveiled, as our main results seem to be largely driven by mechanical industries.

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