# Automation Adoption and Export Performance: Evidence from French Firms

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**Abstract**

This paper examines the impact of the adoption of automation technologies on the export performance of French firms. We adopt a staggered difference-in-differences design (Callaway and Sant'Anna, 2021) exploiting the lumpiness of imports of products incorporating automation technologies and the timing of the adoption event across firms. We find that after an automation spike, there is actually a decrease in export performance (export value, number of exported products, and number of export markets). We propose two potential explanations for these findings: (i) changes in the product mix after automation and (ii) a reallocation of innovation efforts from product to process innovation. The results highlight the complex effects of automation on firms' export portfolios and suggest a potential trade-off between process and product innovation.

**Keywords**: Automation, exports, multiproduct firms, innovation
**JEL Codes**: L11, L22, L25

# 1 Introduction

The discussion around the impact of emerging automation technologies has primarily centered on their potential effects on employment, such as the displacement of labor and the vulnerability of specific worker groups (Frey and Osborne, 2017; Nedelkoska and Quintini, 2018; Acemoglu and Restrepo, 2020; De Vries et al., 2020; Domini et al., 2021). However, less attention has been paid to how these technologies affect trade (Artuc et al., 2022; Alguacil et al., 2022; Lin et al., 2022) and the broader configuration of global production. Indeed, automation technologies enable firms to create customized products suited to diverse market preferences, enhance product quality by minimizing production errors, and optimize technical processes (DeStefano and Timmis, 2021; Lin et al., 2022). They also potentially facilitate reshoring, making it more economical to bring production back from low-wage countries using automated processes (Faber, 2020; Krenz et al., 2021).

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Previous research on the topic has primarily focused on the impact of specific automation technologies, such as robots, on overall export performance (Artuc et al., 2022; Alguacil et al., 2022; Lin et al., 2022). However, there is limited research on the effects of other 4IR technologies, such as 3D printers (Freund et al., 2022), on export outcomes. Furthermore, while some studies have examined the relationship between automation and export quality (DeStefano and Timmis, 2021; Lin et al., 2022), there is a lack of evidence on how automation adoption influences firms' export portfolios, including the number of products exported and the number of destination countries served.

In this paper, we address these gaps using French firm-level data from 2002–2019 to explore how various automation technologies affect multiple outcomes of exports, including total value, number of products, number of destination countries, quality and price. Our descriptive analysis suggests that firms adopting automation technologies experience higher growth rates of export value, number of exported products, and number of export destinations compared to non-automating firms. However, these results may be driven by differences between automating and non-automating firms (i.e. selection into automation) rather than the effect of automation *per se*. To address this issue, we employ a difference-in-differences design exploiting the timing of imports of automation across adopting firms. Focusing on the sample of automating firms, we find that after an automation spike, there is actually a decrease in export value, number of exported products, and number of export markets. These effects are consistent across both core and non-core products, regardless of the income level of the target markets, though the impacts vary by type of automation technology and industries.

This suggests changes in the export product mix (Mayer et al., 2021; Bontadini et al., 2023) or a potential shift in firms' focus from product to process innovation (Antonioli et al., 2022).

Our work contributes to two strands of literature. First, we contribute to the literature on the sources of export performance at the firm level. Automation can indeed improve firm capabilities and ability to upgrade their products (Szalavetz, 2019). In particular, robots can improve efficiency (Acemoglu and Restrepo, 2019). Robot technologies can also lower production errors, hence lead to higher quality of exported products. DeStefano and Timmis (2021) use industry-country data and show that adopting robots increases export quality. These results are mainly driven by quality increases in developing countries, via a switch from low-quality to high-quality exported products. Similarly but at the firm level, Lin et al. (2022) find that robot adoption promotes quality upgrading of Chinese firms, as driven by an increase in labour productivity and human capital level. The study by Alguacil et al. (2022) analyses instead the effect of robot adoption on general export performance in a sample of Spanish manufacturing firms from 1990–2014. They find that robot adoption increases export probability, export sales and the share of exports in total output. They argue that this result is explained by the increase in total factor productivity, product innovation, and imports.

Our firm-level analysis further explores how the product adjustment after automation influences the product portfolio (Mayer et al., 2021) and the ability of firms to introduce new products. Via automation, firms can develop customized products (Faber, 2020; Krenz et al., 2021; Artuc et al., 2022). For example, the introduction of 3D printing boosted exports of producers of hearing aids (Freund et al., 2022; Weller et al., 2015). On the other hand, according to Antonioli et al. (2022) automation could divert firms' resources away from product innovation and thus limit their ability to offer new products. According to our preliminary results, it seems that automation adoption decreases the number of products, especially new products, while it does not increase product quality. This is in line with the work by Antonioli et al. (2022) highlighting the possible substitution effects between automation and innovation investments.

Second, this paper also contributes to the literature on the firm-level effects of automation, and the benefits and challenges of adopting such technologies. 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 preliminary results. Section 6 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 or 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 retrieve 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 of transactions, average export over number of products, and share of exports over total sales.

### 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. The exception is represented by countries for which statistical offices have started collecting (survey) data on adoption. For instance, Bessen et al. (2020, 2023) use automation costs reported by firms in a Dutch firm-level survey. In the United States, the U.S. Census Bureau and U.S. National Center for Science and Engineering Statistics (NCSES) conduct an annual business survey that provides comprehensive and timely information on the adoption and diffusion of advanced technologies, including artificial intelligence, cloud computing, robotics and the digitization of business in U.S. firms (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.

Domini et al. (2021, 2022) also explain some potential limitations of this measure, including the possibility of false negatives, as firms may buy automation technologies domestically instead of internationally or use intermediaries rather than import automation technologies, and false positives, as firms importing capital goods embedding automation technologies may re-sell them. On the first point, as argued in Domini et al. (2021), France has a comparative disadvantage in producing automation technologies so imports are the most important source for adoption; and the use of intermediaries is less likely for complex goods (Bernard et al., 2015). On the second point, Domini et al. (2021, 2022) successfully run robustness checks excluding possible resellers.

## 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). 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. Finally, we focus our analysis on manufacturing firms.

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, 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 | 2,740,986 | 503,665 |
| - of which, manufacturing | 629,099 | 66,569 |
| Importers of automation (adopters) | 647,304 | 55,375 |
| - of which, manufacturing | 283,714 | 22,386 |

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** | *** |
| Log unit price | **1.33** | 1.30 | *** |
| Quality-adjusted price | **1.22** | 1.05 | *** |

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

This section describes our empirical strategy. After showing that automating firms and non-automating firms are on different trends in subsection 3.1, we describe our event-study approach, focussing on adopting firms only in subsection 3.2.

## 3.1 Comparing automating firms to non-automating firms

First, we explore how automating firms differ from non-automating firms. In the previous section, table 2 shows 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 terms of firm characteristics such as size, as well as export performance. In a difference-in-differences design, 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, run on a sample including both adopting and never-adopting firms:

$$\Delta Y_{it} = \beta A_i + \gamma X_i + \delta_t + \epsilon_{it} \tag{1}$$

where $Y_{it}$ is one of the outcome variables of interest, including export outcomes, including exports value, number of countries, number of products, quality, quality-adjust price and unit price. $A_i$ is a dummy denoting whether a firm ever adopts over the 2002-2019 period, $\delta_t$ is a year effect, and $X_i$ are additional controls for firm-level characteristics including sector dummies,[1] and $\epsilon_{it}$ is the error term.

The coefficient of interest is $\beta$, which tells us whether automating firms show different trends in the variables of interest. The results from this exercise, shown in the next section, will reveal significantly different trends between automating firms and non-automating firms.

### 3.2 Event study on automating firms

As our automation spike variable represents 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. This popular methodology has been used in several papers related to firm-level outcomes of automation (e.g. Domini et al., 2022; Bessen et al., 2020)), in addition to vast policy evaluation literature (e.g. Markevich and Zhuravskaya, 2018; Bosch and Campos-Vazquez, 2014; Lafortune et al., 2018).[2] The classic two-way fixed-effects (TWFE) event-study specification reads as follows:

$$Y_{it} = \alpha_i + \sum_{k \neq -1; k_{min}}^{k_{max}} \beta_k D_{it+k} + \delta_t + \epsilon_{it} \tag{2}$$

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, $\alpha_i$ is a firm fixed effect, $\delta_t$ is a year effect, and $\epsilon_{it}$ is the error term. Coefficient $\beta_k$ 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 $k_{min} = -5$ and $k_{max} = 5$, meaning that our $\beta_{-5}$ refers to the average outcomes three or more years prior to 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

[1] We also consider different specifications, including baseline-level controls of the dependent variables and employment. All lead to similar and, if anything, more clear-cut results.

[2] Roth (2022) find that between 2014 and June 2018, there are 70 total papers that include a figure as an event-study plot in papers published in the *American Economic Review, American Economic Journal: Applied Economics*, and *American Economic Journal: Economic Policy*.

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. Results from equation 1 imply that choosing non-adopters as a control group would not satisfy the PTA. Hence, as 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. It means we use not-yet treated firms as control group. We will show that the outcome variables' trends before treatment do not appear to differ across firms depending on treatment timing, hence firms treated at a later point can be argued to represent a good counterfactual for what would happen in the absence of treatment.[3]

As for the no-anticipation assumption, it may be plausible to different degrees, depending on the specific outcome variable at hand (e.g. product diversification vs export value). Furthermore, 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, as mentioned above, 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 consist of a weighted average of many different 2×2 comparisons between a group that receives treatment at a certain time and another group used as control. Some of these will be "bad comparisons" using already-treated units as control units. The coefficients on the leads and lags of the treatment 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).

[3] See footnote A.

We adopt the estimator by Callaway and Sant'Anna (2021) (CS), 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

## 4.1 Comparing automating firms to non-automating firms

### 4.1.1 Difference-in-differences design

The results from the regression as per Equation 1, displayed in table 3, show that there are significant differences in trends between adopters and non-adopters. Compared to non-automating firms, automating ones have 3.1 % higher changes in (log) export value. Positive differences are observed also for changes in export countries and exported products, and negative ones for prices, although results for the latter show lower statistical significance.[4]

These differences in the trends of the outcome variables between adopting and non-adopting firms suggest that the PTA is unlikely to hold for the latter, hence justify our decision to conduct our event study on a sample that only includes adopting firms, exploiting treatment timing for identification as not-yet treated observations constitute the control group. In Appendix A, we show that pre-trends in the outcome variables do not seem to differ for firms treated at different points in time, which suggest that the PTA may hold when using not-yet treated observations as control group.

Table 3: Comparing automating non-automating firms: Estimation of Equation 1.

| | Export value (log) | Number countries | Number products | Quality | Quality-adj. price | Unit price |
|---|---|---|---|---|---|---|
| D | 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 |

Note: *, **, and *** denote $p < 0.10$, $p < 0.05$ and $p < 0.01$, respectively, based on SEs clustered at the firm level.

[4] If post-treatment observations are removed, coefficients are even larger and more significant.

### 4.1.2 Event study comparing treated and never treated

[TO DO: Trang] do event study with never treated and show that we have a pre-trend problem

In what follows, we use the event study specification 2 using Callaway and Sant'Anna (2021). Figure 1 plot the event study coefficients for log exports, probability of exports, log number of countries, log number of products, log unit price, and log average exports per product. We find no evidence of selection into automation adoption based on past firm growth in exports, number of countries, number of products, and unit price if we condition for parallel trends based on 2-digit sector, log number of employees, log sales, log labor productivity and their commuting zones. The event study figures for probability of exports and log average exports per product may have pre-trends problems, but we will check these pre-trends problems in our next step using honest differece-in-difference based on method suggested by Roth (2022).

After firms adopt automation, their export values increase slightly from year of the event to year 2 after the event. From year 3 to year 5, the main coefficient is positive and larger in magnitude, but remains statistically insignificant. Only from year 6, the main coefficient is positive, even larger from year 3-5, and statistically significant. From year 6, their export values increase by around 11.3% compared to 1 year before the event and compared to firms that never adopt automation technologies. The coefficients remain positive and significant 10 years after the automation adoption event. This increase in export is driven by number of countries exported and average exports per product, rather than by number of products and unit price. We see an increase and statistically significant in number of countries after automation adoption event. At year 3, firms expand their exports by 2.9% more compared to 1 year before the event and compared with firms that never adopt automation. This increase continues in long-term, and by year 10, firms increase their number of exported countries by around 7.6% more. Firms do not change their exports portfolio, neither dropping or increasing their exports product portfolio. There is a sign that in short-term, firms may reduce their export portfolio, but then after that they return to the same number of products before automation event, and in long-term, they may increase by 1%, but these coefficients are not statistically significant. The increase in export, instead, is driven by average exports per product, when around 6 years after automation event, firms increase their average exports per product by around 10.4% compared to the year before the event and compared with never-treated group. This increase is long-lasting, lasts at least until year 10 after the event. Firms keep exporting more over the next years until reaching a plateau at 20% higher exports, 9% more number of countries, and 20% higher average exports per product. Although we find an increase in intensive margin (exports value), the extensive margin (probability of exports) see an increase only in short term at year of the event and 1 year after the event at around 1.2%. However, this increase might happen even before the event, and around 3 years after event, probability of export does not change, and have a tendency to decrease over time, reaching a plateau of around -1% 10 years after the event. However, these coefficients from year 2 onwards are not statistically significant. We can say that after automation adoption event, firms keep exporting more over the next years until reaching a plateau at 17.2% higher exports, 7.6% more number of countries, and 16.1% higher average exports per product after 10 years of adoption, and no significant change in probability of exports, number of products, and unit price. Figure 2 provides additional evidence on share of exports over sales, and we do see an increase in share of exports over sales after automation event and become statistically significant around 4 years after the event, and reach around 2% more 9 years after adopting automation. Table 5 provides additional details.

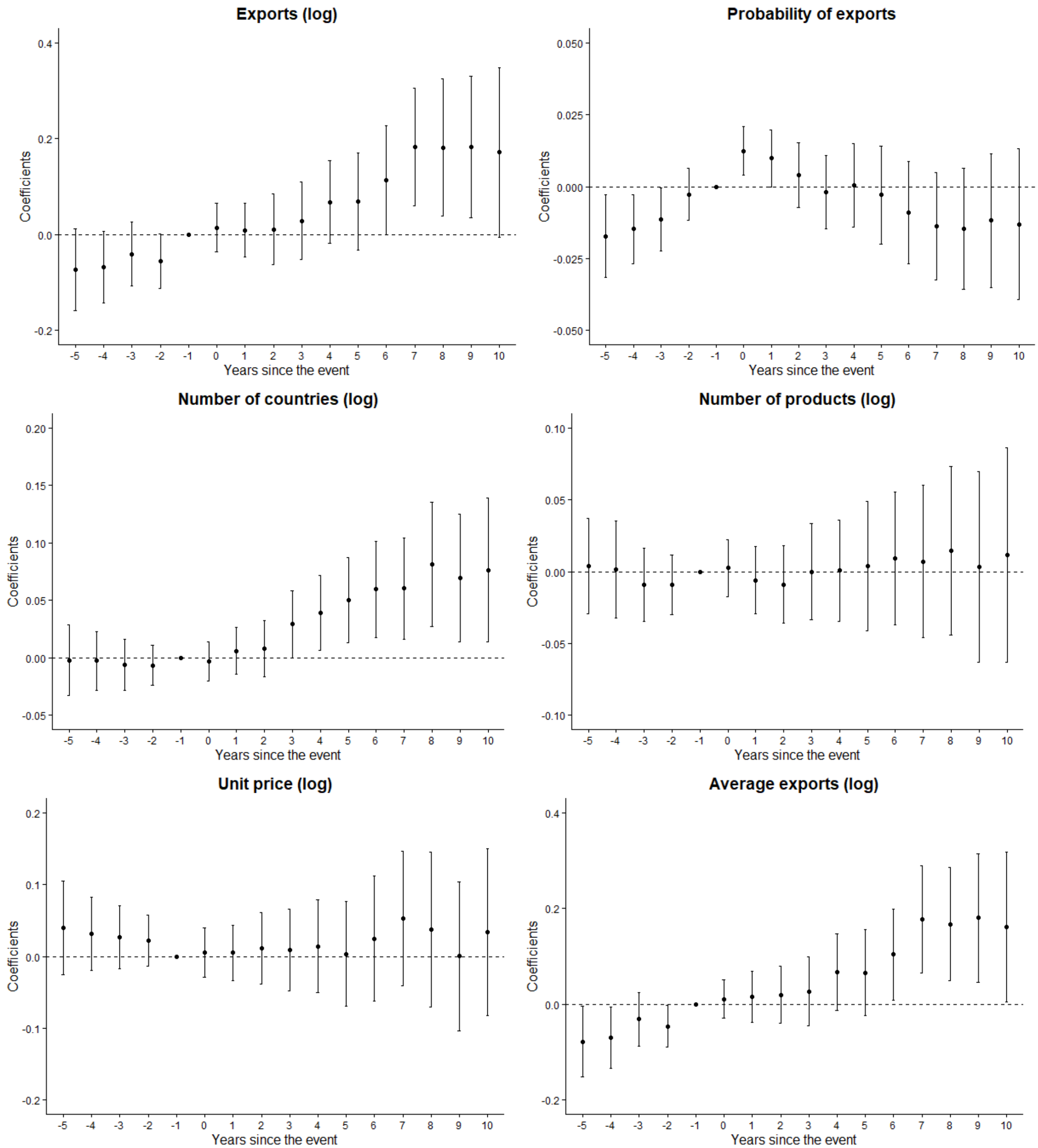


Figure 1: Various export outcomes around automation spikes (never treated, with controls, unbalanced panel).

Note: Figure 1 plots the estimated $\beta_k$ event study coefficients from a regression of the form given in equation 2 using Callaway and Sant'Anna (2021), where the dependent variable is, in turn, log total exports, probability of exports, log number of countries, log number of products, log unit price, log average exports per product. The event is defined as an automation spike. The control group is never treated observations. $\beta_{-1}$, the coefficient of the year prior to an automation spike of a firm, is normalized to zero. The vertical lines represent 95% confidence intervals. We condition for parallel trends using 2-digit sector, log number of employees, log sales, log labor productivity and their commuting zones.

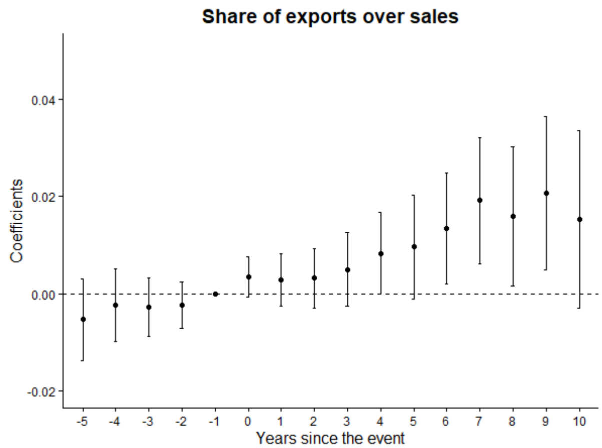


Figure 2: Share of exports over sales around automation spikes (never treated, with controls, unbalanced panel).

Note: Figure 2 plots the estimated $\beta_k$ event study coefficients from a regression of the form given in equation 2 using Callaway and Sant'Anna (2021), where the dependent variable is share of export over sales. The event is defined as an automation spike. The control group is never treated observations. $\beta_{-1}$, the coefficient of the year prior to an automation spike of a firm, is normalized to zero. The vertical lines represent 95% confidence intervals. We condition for parallel trends using 2-digit sector, log number of employees, log sales, log labor productivity and their commuting zones.

Table 4: Main results

| | Log exports | Probability of exports | Log nb of countries | Log nb of products | Log unit price | Log average exports | Share exports over sales |
|---|---|---|---|---|---|---|---|
| Automation | 0.149*** | -0.006 | 0.070*** | 0.018 | 0.027 | 0.132*** | 0.014*** |
| | (0.032) | (0.005) | (0.014) | (0.016) | (0.026) | (0.032) | (0.003) |
| Nb of obs | 306,856 | 525,125 | 308,412 | 308,412 | 306,856 | 306,856 | 302,042 |

Table 5: Main results

| | Log average exports by country | Log average exports by country product |
|---|---|---|
| Automation | 0.079* | 0.062* |
| | (0.029) | (0.029) |
| Nb of obs | 306,856 | 306,856 |

**IV design** To establish a valid instrument, it is necessary to ensure that it is correlated with the automation adoption variable at the firm level while remaining uncorrelated with any factors that might influence firm exports, once various controls are accounted for. Following the methodology of Bonfiglioli et al. (2020), Wang et al. (2024), Artuc et al. (2022) we construct an instrumental variable based on the premise that higher automation adoption aligns with greater technological feasibility and practical applicability. In addition, we use commuting zones age to proxy for the labor force age in a commuting zone. Specifically, we use data on the prevalence of automation adoption in production within an industry which varies over time, combined with information on the initial ease of worker replacement with automation for a given firm, and with initial labor force's age structure in a commuting zone.

First, we calculate the ratio of automation-adopting firms, excluding the focal firm, to the total number of firms within a specific industry in a given year. This ratio serves as an indicator of the technological suitability of certain industries for automation adoption, which we call "Prevalence". Next, we create an initial task replaceability index at the firm level, measured in year 2002 - the year beginning of our dataset, termed "Replaceability". This index captures the idea that within a specific industry, automation are more commonly adopted by firms whose employees initially predominantly engage in manual tasks.

To generate this firm-level measure of initial task replaceability, we follow a two-step process. First, we manually match the occupations in each sampled firm with the U.S. Census occupations classification provided by Autor and Dorn (2013), which measures the intensity of manual task input for each occupation. Then, we calculate the aggregated intensity of manual task input for all occupations within a firm, weighting it by the initial employment share of each occupation.

Third, we calculate labor force's age structure in a commuting zone, measured by the share of employees aged 56 and above over the total number of employees. We choose 56 at our threshold, following the approach by Acemoglu and Restrepo (2022).

Our instrumental variable, *Auto_Exposure*, is thus defined as follows:

$$\text{Auto\_Exposure}_{it} = \text{Prevalence}_{s-i,t} \times \text{Replaceability}_{i,2002} \times \text{CZ\_Age}_{c,2002} \tag{3}$$

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

By establishing a source of firm-level variation in automation exposure, our instrument is correlated with automation adoption at the firm level. We later verify the relevance condition in the first-stage regressions of the IV estimation. For the exclusion restriction, our identifying assumption is that the instrument, Auto_Exposure, does not affect firm-level export outcomes through channels other than the automation adoption of firms.

The first component of the instrument, Prevalence, assesses the technological feasibility of automation adoption within a specific industry, which is unlikely to be influenced by individual firm behavior once the focal firm is excluded. The second component, Replaceability, reflects the practical applicability of robots in a given firm based on the initial occupational characteristics related to the intensity of manual task input. Therefore, our instrument measures the probability of automation adoption for a given firm within a particular industry from a technological perspective.

Table 6: Automation adoption and exports: IV estimates (never treated).

| | Log exports | Probability of exports | Number of countries | Number of products | Log unit price | Log average exports | Share exports over sales |
|---|---|---|---|---|---|---|---|
| **Panel A: Automation adoption** | | | | | | | |
| Second stage | 1.000*** | 0.026 | 0.176*** | 0.126** | 0.409*** | 0.878*** | 0.132*** |
| | (0.134) | (0.021) | (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) |
| First-stage F-statistic | 452 | 452 | 452 | 452 | 452 | 452 | 452 |
| Firm FE & Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 311,058 | 518,934 | 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.

Table 7: Automation adoption and exports: IV estimates (never treated).

| | Log avg exports by country | Log avg exports by country product |
|---|---|---|
| **Panel A: Automation adoption** | | |
| Second stage | 0.827*** | 0.704*** |
| | (0.109) | (0.102) |
| First stage: Dependent variable is *Automation* | | |
| *Automation_exposure_i,t* | 0.006* | 0.006* |
| | (0.004) | (0.004) |
| First-stage F-statistic | 452 | 452 |
| Firm FE & Year FE | Yes | Yes |
| Observations | 311,058 | 311.058 |

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

#### 4.1.3 How important is the pre-trend problem? A check using the Honest DiD approach.

In the section ??, we implemented an event study approach to assess the impact of automation adoption event on several dimensions of firms' exports outcomes over time. We use the approach by (Callaway and Sant'Anna, 2021) to account for treatment effect heterogeneity, meaning to account that the effect of the reforms might vary across different groups. However, a key assumption in difference-in-differences analysis, and also in staggered event study, is that in the absence of the treatment (automation adoption event), the trends in the outcomes (firms' exports outcomes) for the treated group (adopted firms) and the control group (never adopted firms) would have been the same. If this assumption is violated, the estimated treatment effect might be biased.

Therefore, we implemented the method by (Roth, 2022) to test how sensitive the results are o possible violations of the parallel trends assumption. Specifically, it allows for some deviations from the assumption and measure how much deviation would be needed to change the results significantly. There are constraints that limit how much the trends can differ between consecutive periods. By varying the amount of allowed deviation (parameter $M$), the robustness of the results is tested. We use credible confidence sets which are intervals that provide a range of values within which the true effect is likely to fall, considering possible deviations from the parallel trends assumptions.

Figure ?? plots the original OLS confidence intervals for the five post-treatment period with an original effect (in red) and the robust confidence sets (in black). [5]. We use different values of $M$, where $M = 0$ allows for linear trend deviations and higher values allow for larger deviations. The red line indicates the original OLS confidence interval for the five-year post-treatment period with a not significant effect. The black lines show robust confidence sets for different $M$ values. These show how robust the results are to deviations from the parallel trends assumption. The estimated effect on export value is robust to both linear and non-linear deviations with a breakdown value of $M$ equal to 0.4 (as $M$ increases, the confidence intervals still show a not statistically significant effect). The null hypothesis (no effect) cannot be rejected as long as we not allow for deviations beyond $M = 0.4$. If we believe that the deviation from the linear trend is less than or equal to 0.4 percentage points, the estimated effect is considered robust and not significant. If the deviation is larger than 0.4

[5]We implemented these confidence sets using the honestdid Stata command. We used the average pre treatment effects as the five-year pre-treatment period and the average post-treatment effects as the five-year post-treatment period.

percentage points, the robustness of the result still may be questioned.

## 4.2 Do the characteristics of products and destinations matter?

The results just shown need not be uniform across different types of products and destination countries; in fact, they may be driven by some of these.

Automation's effect on exports might vary between core products, which are central to a firm's business, and non-core products [ADD REF]. Firms might reduce exports of non-core products to become more specialized in core products, therefore, we might expect firms that the effect of automation technologies on decreasing exports, may be even more substantial for non-core products.

The impact of automation technologies on exports also depends on the economic status of the target markets - however the impact here is not clear-cut. On one hand, high-income countries, which often demand advanced and high-quality products, may make firms to more focused on these countries with the help of automation technologies to adjust the demand from these countries. On the other hand, lower-middle-income countries might prioritize cost over quality, automation technologies could help to produce these products more standardized and in a reduced time period. We now provide some exploratory evidence on this by showing how results differ between types of technologies, industries, exported products, and destination countries.

### 4.2.1 Core vs Non-core products

The results from the heterogeneity analyses on core vs non-core products are shown in Figure **??**. We define core product as product with largest share in a firm's total exports, and other products as non-core products. The data indicates that the export values for both core and non-core products exhibit a similar declining trend following the automation event, with no significant differences between the two categories.

Figure **??** presents the results for our intermediate and final exports. Final exports are defined as products within the same 3-digit sector as the firm, while intermediate exports include all other products. A striking difference is observed: the baseline results are mainly driven by a decline in intermediate exports, whereas final exports increase in years t+1, t+2, and t+3 following an automation spike.

Table 8: Characteristics of products and Destination countries

| Dep var: | Exports (log) |
|---|---|
| Panel A. Characteristics of products | |
| Panel A1. Only Core Products | |
| Automation event | 0.117*** |
| | (0.031) |
| Obs | 306,799 |
| Panel A2. Only Non-core Products | |
| Automation event | 0.172*** |
| | (0.039) |
| Obs | 215,235 |
| Panel B. Types of destination countries | |
| Panel B1. Only High-income countries | |
| Automation event | 0.165*** |
| | (0.035) |
| Obs | 275,158 |
| Panel B2. Only Non-high-income countries | |
| Automation event | 0.101** |
| | (0.031) |
| Obs | 402,347 |

### 4.2.2 Types of destination countries

The impact of automation on exports varies with the economic status of the target markets, but the effects are not straightforward. High-income countries often seek advanced and high-quality products, therefore, firms adopting automation technologies might meet these demands and focus their exports on these countries. On the other hand, non high-income countries usually value cost over quality. Here, automation can help produce standardized products more quickly and efficiently, and could help automating firms to prioritize these countries too.

Results considering exports to high-income countries only and non high-income countries only - which are not displayed in the interest of conciseness - show no significant differences between exports to high-income countries and to non-high-income countries. This confirms that the decreasing trend of exports value is not driven by exports to destination countries, but more relevant when examining the impacts for types of technologies, industries, firms and types of exports (intermediate vs final exports).

## 4.3 Do the characteristics of firms matter?

- Adopted technology and industries

- Firm characteristics: Innovation status, Complexity of the firm's products, Productivity, size

### 4.3.1 Types of technologies

For instance, 3D printing may revolutionize exports in industries that demand customization and precision, such as specialized machinery parts. Robotics, on the other hand, might be more beneficial in industries with repetitive and voluminous production tasks.

We focus our analysis on two types of technologies that are expected to create disruptions in the trade and global value chains.3D printing are expected to a gradual replacement of international trade (Abeliansky et al., 2020), while Freund et al. (2022) find that exports of hearing aids increased following the introduction of 3D printing. Robot adoption might increase imports and exports from less developed countries (Artuc et al., 2022). Figure **??** shows our results for adopting 3D printing or robots only for French firms in our sample between 2002 and 2017.

An interesting difference emerges if we focus on robot spikes instead of automation spikes. In other words, if instead of using our broad automation measure we focus on a single technology, namely robots, one that has received most of the attention of the literature. In this case, no significant change in the export value is detected after a spike. For 3D printing spikes firms, we also only see a clear decrease and statistically significant three years after the event, while for the other years, the coefficients are more noisy. This difference from the main exports points to the presence of heterogeneity across different technologies.

### 4.3.2 Types of industries

We focus our analysis on two industries—textiles and machinery—where the impact of automation on export outcomes is expected to be significant (for other industries, see Appendix D). The potential for automation to affect exports varies widely across industries. Textile manufacturing highlights these challenges: the sewing process requires human qualities such as intuition and dexterity that are difficult to automate. On the other hand, tasks in automobile assembly lines have been more easily automated. This automation has helped to reduce errors and improve the consistency of repetitive tasks in car manufacturing (Graetz and Michaels, 2018; De Vries et al., 2020). Figure **??** presents our findings on the adoption

Table 9: Characteristics of Firms

| Dependent Variable: | Log exports | Prob exports | Log nb countries | Log nb products | Log unit price | Log avg exports | Sh ex over sales |
|---|---|---|---|---|---|---|---|
| **Panel A. Types of Technologies** | | | | | | | |
| **Panel A1. Only c-auto technologies** | | | | | | | |
| *Automation event* | 0.007 | -0.028* | 0.044 | 5e-04 | 0.030 | 0.007 | 0.018 |
| | (0.092) | (0.014) | (0.033) | (0.040) | (0.065) | (0.085) | (0.011) |
| *Observations* | 30,587 | 34,671 | 30,637 | 30,637 | 30,587 | 30,587 | 29,805 |
| **Panel A2. Only ttile technologies** | | | | | | | |
| *Automation event* | 0.292 | 0.019 | 0.015 | -0.035 | -0.228* | 0.329* | 0.033 |
| | (0.183) | (0.033) | (0.070) | (0.086) | (0.129) | (0.175) | (0.024) |
| *Observations* | 8,586 | 9,443 | 8,607 | 8,607 | 8,586 | 8,586 | 8,323 |
| **Panel A3. Only wea technologies** | | | | | | | |
| *Automation event* | -0.200 | 0.021 | 0.029 | -0.154 | -0.154 | -0.045 | -0.002 |
| | (0.202) | (0.027) | (0.087) | (0.093) | (0.093) | (0.159) | (0.019) |
| *Observations* | 5,917 | 6,826 | 5,940 | 5,940 | 5,940 | 5,917 | 5,703 |
| **Panel A4. Only ro technologies** | | | | | | | |
| *Automation event* | -0.059 | -0.015 | -0.029 | -0.010 | 0.062 | -0.050 | 0.007 |
| | (0.119) | (0.021) | (0.050) | (0.065) | (0.111) | (0.118) | (0.017) |
| *Observations* | 10,648 | 11,776 | 10,659 | 10,659 | 10,648 | 10,648 | 10,348 |
| **Panel A5. Only ded technologies** | | | | | | | |
| *Automation event* | 0.045 | -0.020* | 0.069* | 0.011 | -0.052 | 0.036 | 0.015* |
| | (0.062) | (0.011) | (0.025) | (0.028) | (0.047) | (0.058) | (0.008) |
| *Observations* | 65,384 | 75,265 | 65,516 | 65,516 | 65,384 | 65,384 | 63,722 |
| **Panel A6. Only w_auto technologies** | | | | | | | |
| *Automation event* | -0.005 | -0.023 | 0.065* | 0.045 | 0.087 | -0.046 | 0.023* |
| | (0.083) | (0.016) | (0.036) | (0.042) | (0.067) | (0.075) | (0.011) |
| *Observations* | 37,681 | 43,793 | 37,738 | 37,738 | 37,681 | 37,681 | 36,622 |
| **Panel A7. Only r_auto technologies** | | | | | | | |
| *Automation event* | 0.129* | -0.002 | 0.063* | -0.02 | 0.030 | 0.148* | 0.024* |
| | (0.064) | (0.009) | (0.027) | (0.029) | (0.050) | (0.058) | (0.009) |
| *Observations* | 64,529 | 73,333 | 64,639 | 64,639 | 64,529 | 64,529 | 62,907 |
| **Panel A8. Only prter technologies** | | | | | | | |
| *Automation event* | 0.206* | -0.039* | 0.045 | 0.051 | 0.103 | 0.157 | 0.035* |
| | (0.119) | (0.016) | (0.048) | (0.051) | (0.082) | (0.104) | (0.015) |
| *Observations* | 20,278 | 22,728 | 20,293 | 20,293 | 20,278 | 20,278 | 19,828 |
| **Panel A9. Only a_da_pr technologies** | | | | | | | |
| *Automation event* | 0.109* | -0.004 | 0.082*** | 0.021 | 0.066* | 0.090* | 0.017* |
| | (0.048) | (0.007) | (0.021) | (0.023) | (0.038) | (0.045) | (0.006) |
| *Observations* | 98,904 | 118,031 | 99,117 | 99,117 | 98,904 | 98,904 | 96,544 |

of automation technologies by French firms in our sample from 2002 to 2017, for textile industries only and for machinery industries only.

We see a clear decreasing trend from machinery industries in terms of export values - which follow the same pattern as our main analysis. However, interestingly, we only see a decrease in terms of export value and statistically significant at two years after the event for firms in textile industry. The results emphasize the heterogeneity in our industry analysis - where it confirms our hypothesis that automation technologies might have more impacts on machinery industries, rather than textile industries in which tasks are harder to automate.

Table 10: Characteristics of Firms

| Dependent Variable: | Log exports | Prob exports | Log nb countries | Log nb products | Log unit price | Log avg exports | Sh ex over sales |
|---|---|---|---|---|---|---|---|
| **Panel B. Types of Industries** | | | | | | | |
| **Panel B1. Only ind1012 industries (food, beverages, tobacco)** | | | | | | | |
| *Automation event* | -0.218* | 5e-04* | -0.071* | -0.133 | -0.012 | -0.083 | -0.015 |
| | (0.103) | (0.020) | (0.051) | (0.057) | (0.071) | (0.108) | (0.010) |
| *Observations* | 29,569 | 54,161 | 29,650 | 29,650 | 29,569 | 29,569 | 32,342 |
| **Panel B2. Only ind1315 industries (textiles)** | | | | | | | |
| *Automation event* | 0.210* | 0.030 | 0.150* | 0.228*** | 0.093 | -0.015 | 0.014 |
| | (0.114) | (0.018) | (0.059) | (0.061) | (0.070) | (0.103) | (0.015) |
| *Observations* | 32,225 | 46,966 | 32,507 | 32,507 | 32,225 | 32,225 | 31,557 |
| **Panel B3. Only ind1618 industries (wood, paper, printing)** | | | | | | | |
| *Automation event* | -0.085 | -0.028 | -0.042 | 0.005 | 0.196* | -0.089 | 0.009 |
| | (0.151) | (0.020) | (0.055) | (0.048) | (0.084) | (0.127) | (0.012) |
| *Observations* | 27,429 | 58,384 | 27,637 | 27,637 | 27,429 | 27,429 | 27,231 |
| **Panel B4. Only ind1923 industries (chemicals, pharma, plastics)** | | | | | | | |
| *Automation event* | 0.194* | -0.004 | 0.076* | 0.033 | 0.078 | 0.161* | 0.023* |
| | (0.100) | (0.013) | (0.036) | (0.035) | (0.066) | (0.083) | (0.009) |
| *Observations* | 56,053 | 83,728 | 56,173 | 56,173 | 56,053 | 56,053 | 55,274 |
| **Panel B5. Only ind2425 industries (metals)** | | | | | | | |
| *Automation event* | 0.011 | -0.007 | 0.054* | -0.005 | -0.066 | 0.016 | 2e-04 |
| | (0.067) | (0.012) | (0.027) | (0.032) | (0.048) | (0.066) | (0.007) |
| *Observations* | 53,863 | 97,998 | 54,048 | 54,048 | 53,863 | 53,863 | 53,022 |
| **Panel B6. Only ind2630 industries (computers, electric, machinery, auto, transport)** | | | | | | | |
| *Automation event* | 0.055 | -0.009 | 0.043* | -0.063* | -0.080* | 0.118 | 0.003 |
| | (0.063) | (0.010) | (0.027) | (0.027) | (0.044) | (0.055) | (0.008) |
| *Observations* | 70,615 | 100,403 | 70,841 | 70,841 | 70,615 | 70,615 | 69,215 |
| **Panel B7. Only ind3133 industries (furniture, other, repairs)** | | | | | | | |
| *Automation event* | 0.145 | -0.026* | 0.121* | 0.110* | -0.189** | 0.042 | 0.006 |
| | (0.100) | (0.014) | (0.042) | (0.040) | (0.080) | (0.096) | (0.010) |
| *Observations* | 37,102 | 84,485 | 37,556 | 37,556 | 37,102 | 37,102 | 36,482 |

### 4.3.3 Types of firms

To further investigate the potential heterogeneity in the impact of automation on export performance, we extend our analysis by considering different types of firms. Specifically, we investigate whether the effects of automation spikes vary systematically across firms of different sizes, innovation propensities, product complexity levels, and productivity.

Figure **??** presents the results of analysis splitting the sample by four firm size classes: very small firms, small firms, medium firms, and large firms. The results show that the negative impact of automation on total export values is apparent in all size classes with the exception of very small firms, where the effect is largely muted. This suggests that very small firms may be less affected by the potential disruptive effects of automation on export performance, possibly due to their limited scale of operations or different production processes.

Figure **??** presents the results of the analysis for innovators, defined as firms with at least one patent in the interval period, and non-innovators. The findings suggest that the negative effect of automation on export values is more pronounced for innovators compared to non-innovators. This result lends support to the hypothesis that the overall negative impact of automation on export performance may be partially driven by a substitution effect between product and process innovation (Antonioli et al., 2024) [6]. Specifically, it is possible that firms that are actively engaged in innovation activities may divert resources away from product innovation and towards process innovation when they adopt automation technologies. This shift in focus could lead to a temporary slowdown in the introduction of new products or the improvement of existing ones, which in turn may negatively affect export values. In contrast, non-innovative firms may be less prone to this substitution effect, as they are less likely to be actively pursuing product innovation in the first place. As a result, their export performance may be less sensitive to the adoption of automation technologies.

Figure **??** further explores the heterogeneous effects of automation on export performance by splitting firms into two groups based on the complexity level of their export portfolio [7]. The results reveal a striking difference between the two groups. For firms exporting highly complex products, the adoption of automation technologies leads to a significant and persistent decline in export values. In contrast, firms exporting products with low complexity experience an increase in export values immediately following an automation spike. This positive effect persists until the fourth year after the event, suggesting that automation may actually boost the export performance of firms with less complex product portfolios. One possible explanation for this pattern is that firms with highly complex products may face greater challenges in adapting their production processes to incorporate automation technologies. On the other hand, firms with less complex products may be better positioned to reap the benefits of automation, such as increased efficiency and reduced costs, without facing the same level of disruption to their production processes. As a result, they may be able to quickly translate the gains from automation into improved export outcomes.

Finally, Figure **??** divides the sample into top and bottom productive firms [8], without showing significant differences among the two.

**Types of firms**: Automation event benefits most more small and medium firms, in terms

[6] Antonioli et al. (2024) find a negative association between robotisation and product innovation for Spanish firms, suggesting that diseconomies of scope, driven by investments that increase capacity, may happen.

[7] We measure complexity level of a firm $i$ at time $t$ as the most complex product that a firm produces in that year $t$.

[8] We define top and bottom productive firms based on their 75th and 25th percentile of productivity levels before the year of the event.

Table 11: Characteristics of Firms

| Dependent Variable: | Log exports | Prob exports | Log nb countries | Log nb products | Log unit price | Log avg exports | Sh ex over sales |
|---|---|---|---|---|---|---|---|
| **Panel C. Types of Firms** | | | | | | | |
| **Panel C1. Only very small firms** | | | | | | | |
| *Automation event* | 0.051 | -0.125*** | 0.074 | -0.007 | -0.097 | 0.06 | 0.012 |
| | (0.171) | (0.026) | (0.066) | (0.073) | (0.155) | (0.136) | (0.019) |
| *Observations* | 16,761 | 32,784 | 16,902 | 16,902 | 16,761 | 16,761 | 16,450 |
| **Panel C2. Only small and medium firms** | | | | | | | |
| *Automation event* | 0.021 | -0.038** | 0.074** | 0.034 | 0.093** | -0.012 | 0.010 |
| | (0.054) | (0.011) | (0.021) | (0.022) | (0.043) | (0.048) | (0.006) |
| *Observations* | 121,757 | 153,698 | 122,152 | 122,152 | 121,757 | 121,757 | 119,474 |
| **Panel C3. Only large firms** | | | | | | | |
| *Automation event* | 0.054 | 2e-04 | 0.046 | 0.082 | 0.035 | -0.025 | 0.016 |
| | (0.115) | (0.014) | (0.049) | (0.060) | (0.111) | (0.113) | (0.015) |
| *Observations* | 20,673 | 21,410 | 20,683 | 20,683 | 20,673 | 20,673 | 20,219 |
| **Panel D. Innovation status** | | | | | | | |
| **Panel D1. Only innovating firms** | | | | | | | |
| *Automation event* | 0.151* | 0.002 | 0.061** | -0.017 | -0.002 | 0.168** | 0.021** |
| | (0.054) | (0.008) | (0.026) | (0.027) | (0.048) | (0.055) | (0.007) |
| *Observations* | 62,565 | 73,241 | 62,670 | 62,670 | 62,565 | 62,565 | 61,615 |
| **Panel D2. Only non-innovating firms** | | | | | | | |
| *Automation event* | 0.153*** | -0.011* | 0.068*** | 0.041** | 0.060** | 0.113** | 0.012** |
| | (0.042) | (0.006) | (0.016) | (0.018) | (0.029) | (0.037) | (0.004) |
| *Observations* | 244,291 | 451,884 | 245,742 | 245,742 | 244,291 | 244,291 | 240,427 |
| **Panel E. Complexity of firm's products** | | | | | | | |
| **Panel E1. Only high complex firms** | | | | | | | |
| *Automation event* | -0.276** | 0.072*** | -0.092*** | -0.239*** | -0.071** | -0.035 | -0.015** |
| | (0.043) | (0.007) | (0.019) | (0.022) | (0.036) | (0.039) | (0.006) |
| *Observations* | 105,102 | 212,745 | 105,381 | 105,381 | 105,102 | 105,102 | 102,460 |
| **Panel E2. Only low complex firms** | | | | | | | |
| *Automation event* | 0.454*** | -0.157*** | 0.139*** | 0.312*** | 0.076 | 0.138 | |
| | (0.107) | (0.019) | (0.037) | (0.032) | (0.095) | (0.104) | () |
| *Observations* | 49,466 | 101,098 | 50,146 | 50,146 | 49,466 | 49,466 | |
| **Panel F. Productivity level** | | | | | | | |
| **Panel E1. Only top productive firms** | | | | | | | |
| *Automation event* | 0.167** | 0.004 | 0.067** | -0.020 | -0.221*** | 0.184** | 0.008 |
| | (0.081) | (0.012) | (0.032) | (0.036) | (0.065) | (0.070) | (0.008) |
| *Observations* | 191,045 | 370,414 | 192,169 | 192,169 | 191,045 | 191,045 | 188,295 |
| **Panel E2. Only bottom productive firms** | | | | | | | |
| *Automation event* | -0.126 | -0.031 | -0.010 | 0.034 | -0.117 | -0.159 | 0.005 |
| | (0.126) | (0.023) | (0.052) | (0.061) | (0.135) | (0.121) | (0.016) |
| *Observations* | 33,847 | 46,971 | 34,030 | 34,030 | 33,847 | 33,847 | 33,113 |

of number of countries - means they are expanding to more markets after automation event (coefficient for number of countries are positive and significant). However, for both very small and small and medium firms, they see a decrease in probability of export after automation. In contrast, we do not see any significant results from large firms.

**Innovation status**: Automation event helps both innovating firms and non-innovating firms in terms of export results. Both see an increase in total exports value, number of countries, average exports, and share exports over sales. The results are comparable between innovating firms and non-innovating firms, except for average exports and share exports over sales where innovating have higher coefficients compared to non-innovating firms. In addition, non-innovating firms see an increase in number of products while we do not see this effect for innovating firms. Non-innovating firms also increase their unit price, but decrease their probability of exports.

- **Resource allocation dilemma**: substitution of product for process innovation [Antonioli et al. 2024]. We add into one more dimension which is types of product innovation. Process innovation might be complementary with product innovation for non-innovating firms, and a substitute for innovating firms.
  - For innovating firms, resources diverted toward automation might reduce their focus on expanding product lines (number of products). They might use automation to scale their existing innovations (intensive margin: stronger effects for export intensity (share export over sales), and average exports per product) rather than developing new products.
  - For non-innovating firms, investing in process innovation (automation investment) is likely a first step for them to compete and expand new product lines (number of products) without requiring significant investments into patents.

**Complexity of firm's products**:
**Productivity level**: We also see different effects for top productive firms and bottom productive firms. Only top productive firms managed to get the benefits from adopting automation. We see that, for top productive firms, adopting automation technologies help them to increase their exports, expand to more countries, increase their average exports per products, and lower their unit price. While for bottom productive firms, we do not see any effects of automation adoption.

- **The Productivity Threshold for Automation Benefits** (Capello et al., 2022). Threshold effects in technology adoption can create false optimism, as adoption levels may appear sufficient but fall short of the critical mass needed for significant productivity gains. Moreover, general-purpose technologies require complementary investments, co-inventions, adjustments, and organizational learning to overcome inertia and bottlenecks.

- The contrast between top and bottom productive firms highlights a productivity threshold that determines the effectiveness of automation. High-productive firms may have the necessary scale, expertise, and resources to integrate automation into their operations, while low-productive firms might lack the complementary factors needed to make automation impactful.

- **Widen disparities between firms** (Bastos et al., 2023). Firms facing greater competition in export markets tend to reduce investments in automation technologies, a trend driven primarily by the least productive firms. In contrast, the most efficient exporters in automation-prone industries are more likely to adopt robotics to stay competitive. This suggests that higher levels of product market competition amplify disparities between firms.
  - In our context, automation appears to reinforce existing disparities between top and bottom productive firms. High-productive firms benefit more, potentially widening the gap between them and their lower-productive counterparts.

## 4.4 Automation and the restructuring of the Global Value Chain

In this part, we report additional results on a possible explanation that reducing exports might be driven by a decrease in imports or vice versa. [9]

### 4.4.1 Automation and total imports

Figure **??** show results for import sides after automation event. All the sub-figures in figure **??** report results for all imports, including automation imports. We see a mirroring trend between imports and exports, when total imports, number of countries, number of products and average imports per product also decrease after automation event. Unit price does not change after automation event.

[9] We do not claim a causality direction here between imports and exports, that a decrease in imports might lead to a decrease in our exports, but an opposite direction could also occur.

### 4.4.2 Non-automation imports

However, non-automation imports might be more interesting to us to see if after automation event, firms also reduce their non-automation imports. We find that this is the case. After automation event, firms reduce their non-automation imports, and this is also the same for share of non-automation imports over sales, as shown in figure **??**.

One possible explanation might be that firms adopt automation technologies to reshore or near shore to somewhere closer to their domestic market. We find that this is not the case when non-automation imports from EU countries in general also reduce after automation event, however, their share of non-automation imports over sales increase over time (after dropping at the year of the event), but the results are not statistically significant.

Table 12: Restructuring of global value chains

| Dependent Variable: | Non-automation imports (log) |
|---|---|
| **Panel A. All firms** | |
| *Automation event* | 0.120*** |
| | (0.030) |
| *Observations* | 326,080 |
| **Panel B. By origin countries** | |
| **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 |

We see that after automation events, firms increase their non-automation imports.

- **Substitution of tasks and expansion of production scales** (Artuc et al., 2022): Robotization affects global trade and labor markets through two key mechanisms: task substitution and prodution scale expansion. Robots replace human labor in tasks where automation is feasible, reducing production costs in high-labor-cost regions like the North and boosting their competitiveness. This leads to increased exports from the North and shifts in trade patterns, as some imports from the South are substituted by domestic production. However, robotization also expands the scale of producton, increasing th edemand for intermediate inputs, including those sourced from the South. Empirical findings from Artuc et al. (2022) and Freund et al. (2022) suggest that the second mechanism-production scale expansion-plays a more dominant role.

Some suggest that automation could lead to reshoring (Faber, 2020; Krenz et al., 2021), but our findings indicate that the expansion of production scales plays a more dominant role. Automation increases imports from non-EU countries, likely due to their cost and price efficiency, while showing no evidence of reshoring—imports from EU countries actually decline after automation events. These results are consistent with findings from Stapleton and Webb (2020); Artuc et al. (2022); Freund et al. (2022).

## 4.5 Robustness checks

In this section, we conduct a series of robustness checks to ensure that our main results are not driven by specific choices in the empirical setup or by potential confounding factors.

First, we address the concern that the observed changes in export performance following automation spikes may be influenced by demand conditions in the destination markets. To control for this possibility, we include a measure of demand growth in each firm's export destinations.

Second, we test the sensitivity of our results to alternative definitions of automation spikes. Specifically, we experiment with different thresholds for identifying significant increases in automation investment, such as using a higher percentile cutoff or a minimum absolute value of automation imports.

Third, we exclude potential re-exporters from our sample to mitigate the concern that our results may be influenced by firms that do not directly engage in production but instead import and re-export products.

Finally, we conduct our analysis using unbalanced panel, rather than balanced panel. Using unbalanced panel, once again, confirms our results, however, the result might have pre-trend problems.

Overall, the robustness tests presented in this section provide strong support for the validity of our results and reinforce the conclusion that automation has a significant impact on firms' export performance, with the direction and magnitude of the effect varying across different types of firms and products.

### 4.5.1 Event study comparing treated and not yet treated

Figure 9 shows event study plots for our seven variables of interest, within the group of automation adopters. More precisely, it plots the estimated $\beta_k$ event study coefficients from a regression of the form given in equation 2 using Callaway and Sant'Anna (2021), where the dependent variable is, in turn, log total exports, probability of exports, log number of countries, log number of products, log unit price, log average exports, and share of exports over sales. Firms turn out to reduce their export value from one year after the shock onwards. This total effect amounts to 20% after 5 years, and could be explained by changes in the extensive or the intensive margin of exports. Considering first the extensive margin, we see that the probability of exporting decreases slightly (coefficient is 0.01) but significantly after the automation event, compared to firms which do not yet automate. The number of export countries and exported products also decreases: firms thus become more specialised. For what concerns the intensive margin (the value for each exported product), coefficients on prices are largely insignificant, although pointing to a positive direction. Finally, the average value of exports (total export value divided by the number of products) significantly decreases. This points to a change in the quantity sold per product line, in a addition to a significant reduction in the range of the portfolio (number of products and destinations) itself. We see an increase in share of exports over sales at the year of the event, but decrease right after, and statistically significant at year t+2 or year t+4 as shown in 8.

Compare with not-yet group, but conditioning on log number of employees, log productivity, division, and commuting zones.

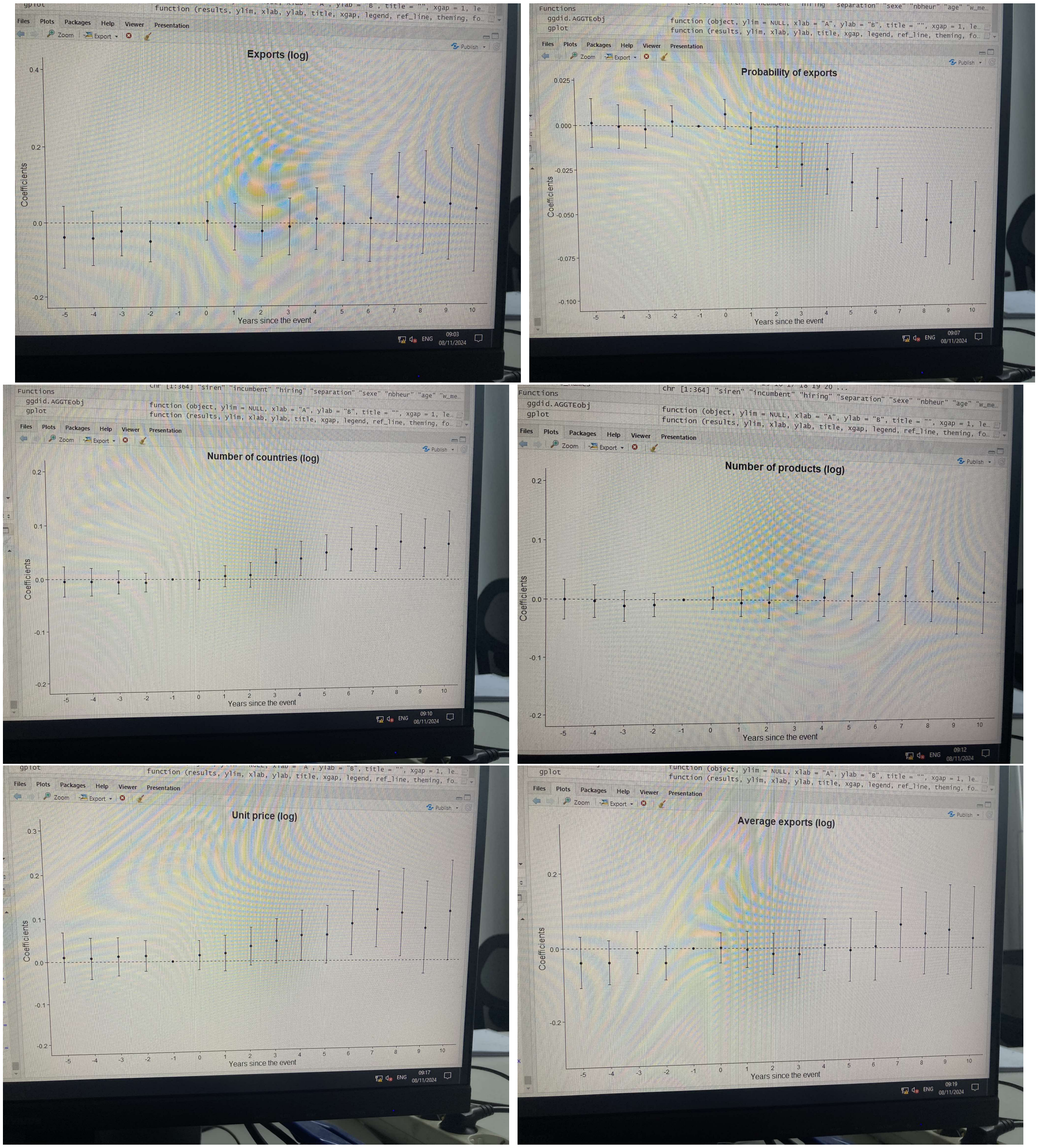


Figure 3: Various export outcomes around automation spikes (not yet treated, with controls, unbalanced).

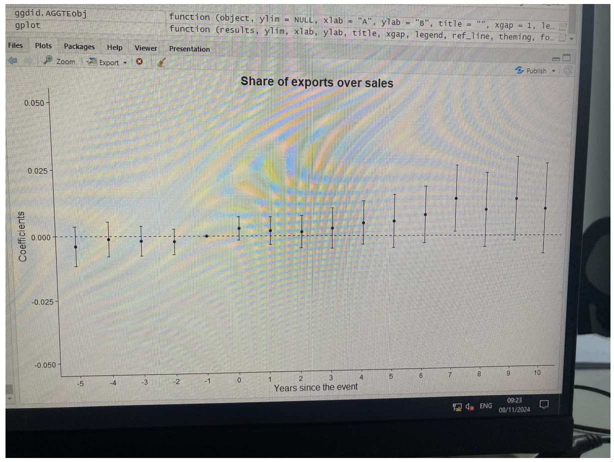


Figure 4: Share of exports over sales around automation spikes (not yet treated, with controls, unbalanced).

#### 4.5.2 Control for demand growth in destination countries

Some might argue that firms decide to automate after experiencing a positive trend in export volume and diversification. If this is the case, our results could have a problem of reverse causality. To address the potential concern of reverse causality, for each firm, we construct a measure of trade-weighted GDP growth in key export partners. In this way, we could address the problem of reverse causality and account for exogenous demand. After controlling for trade-weighted GDP growth in key export partners, exports trend is still similar to our baseline result.

#### 4.5.3 Alternative definition for automation event - Bessen definition

(Bessen et al., 2023) define an automation spike in year $t$ as occurring when automation costs are at least three times the average firm-level cost share. We adjust this definition to fit our setup. Figure **??** presents the results of our baseline regression when restricting the automation spikes to those with a ratio above 3, confirming our results once again.

#### 4.5.4 Removing re-exporters

Our analysis assumes that the automation-investment products imported by firms are also used and adopted in their production processes. However, some firms that import automation

Table 13: Robustness Check

| Dependent Variable: | Log exports | Prob exports | Log nb countries | Log nb products | Log unit price | Log avg exports | Sh ex over sales |
|---|---|---|---|---|---|---|---|
| **Panel A. Control for demand growth in destination countries** | | | | | | | |
| *Automation event* | 0.152*** | | | | | | |
| | (0.030) | () | () | () | () | () | () |
| *Observations* | 243,438 | | | | | | |
| **Panel B. Alternative destination for automation event - Bessen definition** | | | | | | | |
| *Automation event* | | | | | | | |
| | () | () | () | () | () | () | () |
| *Observations* | | | | | | | |
| **Panel C. Removing re-exporters** | | | | | | | |
| *Automation event* | | | | | | | |
| | (0.009) | (0.007) | () | () | () | () | () |
| *Observations* | | | | | | | |
| **Panel D. Balanced panel** | | | | | | | |
| *Automation event* | | | | | | | |
| | () | () | () | () | () | () | () |
| *Observations* | | | | | | | |

products but then do not adopt and re-export such automation intensive goods, which often known as Carry Along Trade (CAT). If this problem arises, our results for automation adoption and export might be biased.

Ideally, to accurately identify carry-along firms and separate pure re-exporters (non-users) from users who also re-export, we would need information on both production and exports at the product level. We proxy this by excluding firms involved in both importing and exporting automation goods, even if in different years. The results, shown in figure **??**, are consistent with the base results.

#### 4.5.5 Balanced panel

Our main analysis is based on a balanced sample as suggested by Callaway and Sant'Anna (2021). The reason is to avoid the issue of changing group composition across different event times. Using a balanced panel helps to create a balanced aggregation that only aggregate *ATT(g,t)* for groups exposed to treatment for at least *e'* periods. Although using a balanced aggregation ensures the same group composition across different event times - which helps us to ensure robustness, this approach uses fewer groups, and potentially leading to less informative inference. Therefore, we re-check in this part using unbalanced panel. The results are shown in figure **??** and show a similar trend with our baseline results - after an automation event, firms reduce their exports. However, it also shows some differences with our baseline results, for example: firms already reduce their exports at year of automation event, and the results hold similar even after 5 years of adopting automation technologies.

# 5 Discussion

- **Automation adoption and the dynamics of performance within firms** (automation adoption and market pressure: is it because they struggle [cf. Holmes et al. 2012] or instead a proof that they are doing well)
  - adopting firms do better than non adopting before the event
  - return to the mean after adoption (positive pre-trend)
- **Resource allocation dilemma**: substitution of product for process innovation [Antonioli et al. 2024]
- **Switchover disruptions**: The need for complementarity of inputs and difficulty to learn/implement the automation techniques successfully [Mohnen et al. 2021 `https://www.nber.org/system/files/chapters/c13894/c13894.pdf`], but this disruption should be in the short run [cf. Holmes et al. 2012]

## 5.1 Comments from conference in Bari, September 2023

- justify the import measure (what about domestic acquiring of such tehcnologies? What about the relationship between spikes in automation technologies and general spikes in investment) → something on which we do not usually spend much time in slides but we did in previous paper and we have to briefly recall here
- 1) Test the effect on the average export value per product; 2) Test the effect on probability to start exporting (These two suggestions from Alessia Lo Turco). 3) Add measure of absorptive capacity at the firm level (some firms are able to exploit the investment, while others do not) → We did 1) and 2); not sure we want to employ the concept of absoprtive capacity (which refers more to the adoption than to the effects of innovation

- Provocative comment from the keynote Lant Pritchett: Why do you exclude the most obvious explanations, i.e. that firms do take wrong decisions and can screw things up, especially when they make large investments?

### 5.2 Comments from the economics of innovation conference in Milan, September 2023

- (Chiara Franco) we could focus more on the international economics debate; in particular what are changes in other imports after adoption of automation; is there a change in the origin of imports (less imports from peripheral/South countries)? → check changes in origin of imports; check origin of automated machines; evaluate change in positioning in global value chains

- (Marica Virgillito) any difference in the effect for intermediate vs final products? use upstreamness of products to identify change in upstreamness of the firm after adoption →(weighted average of upstreamness of products of the firm) - cf Antras and Chor 2013 https://onlinelibrary.wiley.com/doi/abs/10.3982/ECTA10813

- (Keun Lee) is automation a response to negative shocks? (we treat it as exogenous to the firm but it is not; eg could be a response to labor unions) → way to justify our approach to focus on not yet treated; possibility of difference in the effect between early and late adopters? Are early adopters adopting more radical innovations? (higher market stealing effect) → if anything, late adopters are doing better Are there differences within the group of adopters? → check role of possible characteristics such as previous performance, innovation activity, size... discuss case studies/examples in the text

### 5.3 Comments from internal presentation by Giacomo, September 2023

- Why limiting the analysis to manufacturing? Automation technologies are very relevant also in sectors like agri-food. - I replied that we may still expand the analysis at a later stage.

- Can the Information Technology Agreement affect anyhow our independent or dependent variables? – From a quick search, it seems to me that the items covered are not those that make up our automation measure, with very small exceptions.

- Can we observe service automation? – Prohibitive with the data at our hand. Check heterogeneity across industries. – I agree, we should do it.
- Do we account for re-export? – I replied we did in our first paper; but I believe it is worth doing it again.
- Can we observe purchases of automated capital goods from France? – A classic. . .
- Finally, a suggestion by Tania's colleague Karsten Mau: get in touch with a theoretician to make sense of your results. He named Luca Macedoni, who was there, but whom unfortunately I could not approach since I had to leave soon after my presentation. . .

### 5.4 Comments from presentation by Giacomo in Utrecht, October 2023

- (Anna Salomons): our spikes could represent capital deepening rather than new automation technology adoption
- (Ulrich Zierahn): causality cannot be attributed to automation technology adoption because of other co-occurring firm decision (old comment he already made in April)
- (Ulrich Zierahn): some of the firms in our sample might be just importing 1 year
- (Maria Savona): try to understand the industry-specific drivers of your results (referring to the industry heterogeniety)
- (Others): check if process innovation is occurring; widen the time window; try matching strategy

### 5.5 Comments from CONCORDi, October 2023

- (Dolores Anon Higon (Valencia)): our import-based measure does not capture adoption through domestic retailers. This is important because firms purchasing domestically may count on better post-installation services, which enable them to use effectively the new technologies, whereas those purchasing abroad may not rely on such services - hence the negative performance. She suggested looking at some survey (R&D? CIS?)

to see to what extent firms make use of such services in France, if possible. She also said there is something on this in the Alguacil et al. paper. Furthermore, not looking at domestic purchases leads to selection issues and to our not-yet treated observation being possibly "contaminated" as they may actually be already-treated (after a spike in domestic purchases of automation that we do not observe).

- (Francesco Rentocchini (JRC)), on this point, said that, since we look at spikes, he finds it unlikely that we miss other major adoption events. However, we should try having a size threshold for a spike, to make sure we look at large enough events. Also because in his paper on automation and innovation (Antonioli et al., which we cite) they find a U-shaped relation: the effect is negative for small investments, positive for large ones. In general, he was very "empathic" with our results since they also find puzzling results in their paper. He said that once we have a WP we should let them know so they can cite us :) Btw they have a newer version of the their own paper that we should check.

- (Javier Miranda) (Halle) also made the point about the size of the spike. In general, he invited us to build a convincing story for these very puzzling results. Industry effects may be part of the story: our results are driven by sectors related to mechanics, and the French automotive sector declined in the period we observe.

- (Maarten de Ridder (LSE)) suggested to go for an IV strategy (e.g. leveraging the staggered rollout of broadband connection in France), since we may have a hard time selling counter-intuitive results if they can be argued to be affected to endonegenity bias.

- (Kostas Tsekouras (Patras)) suggested a product-level analysis, in particular looking at how profit margins of different products change.

## 5.6 Skype chat

- Marco reporting on a post by Baldwin: "3D-printing may or may not dominate the future of manufacturing. There is no doubt, however, that advanced manufacturing is reducing the number of intermediate parts. The reason is simple. Each machine in the factory can perform more tasks than before. That means that more tasks are bundled inside each factory. This reduces the shipments of intermediate goods among factories. Defragmentation, in other words, is a natural side-effect of automation."

https://www.linkedin.com/pulse/industrial-production-processes-defragmenting-portrait-baldwin-bcgle/

- (Tania reporting on coversation with John Morrow) yesterday we had John Morrow (https://johnmorrow.info/) as a seminar guest and I also had a bilateral talk with him. He works a lot on multiproduct firms and what drives the changes in their portfolio. He was not surprised by our results and mentioned a couple of papers linking process innovation and reduction of product scope/less product innovation (same argument as Antonioli): first the paper by Dhingra (AER 2013, https://www.aeaweb.org/articles?id=10.1257/aer.103 where reduction in costs are seen as competing with the need to expand product variety; and more indirectly in this paper by Fontagné et al 2023, they link process innovation (to respond to energy cost shock and reduce energy use) to exports: https://www.economic-policy.org/wp-content/uploads/2023/04/Martin-et-al.pdf , and linking to the product mix reallocation literature (Mayer et al 2021 https://direct.mit.edu/rest/article Mix-and-Firm-Productivity-Responses-to). We should add these references in the literature discussion and for the interpretation of our results. This strengthens the discussion I think because it really links to the trade literature. Let me know what you think!

# 6 Conclusion

We employ a rich dataset of French firms between 2002 and 2019 and an event study methodology to study how automation adoption relates to export performance. We demonstrate that automating firms are on steeper growth trends in terms of exports value, number of exported products, and number of export countries, when comparing with firms which never automate. However, after an automation spike, these variables decrease, hence trends tend to flatten. This is reflected by the fact that, within the group of automating firms, we observe a worsening of export performance indicators after the adoption event. The results are similar for core and non-core products, as well as for high-income destinations and non-high-income destinations; whereas no significant decrease is detected for robot spikes and textile industries, pointing to heterogeneous effects across types of automation technologies.

We propose two potential reasons for these results: (i) changes in the product mix (Mayer et al., 2021; Bontadini et al., 2023) and (ii) the reallocation of innovation efforts between process and product innovation. Antonioli et al. (2022) find that robot adoption is associated with a decrease in innovation activities because there is a substitution of product innovation with process innovation (allocation dilemma).

We outline two potential directions for future research. First, since the share of exports in total sales decreases after the event, there could be a change in the focus of the firm from the foreign to the domestic market. Future research with both domestic and foreign firm-to-firm transaction data could help to shed light on this matter.

Second, our results highlight the importance of examining the reallocation of innovation efforts between process and product innovation following automation. Preliminary evidence suggests a shift towards process innovation at the expense of product innovation, particularly in firms that automate heavily. Advanced data collection efforts that capture detailed information on firm innovation activities, product characteristics, and market responses would provide valuable insights into these dynamics.

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# A Appendix: Parallel trends for different adoption cohorts

To support the PTA for not-yet treated observations, we run the following OLS regression on the sample of observations between 3 and 1 years before a spike:

$$\Delta Y_{it} = \beta C_i + \gamma X_i + \delta_t + \epsilon_{it} \tag{4}$$

where $Y_{it}$ is the dependent variable of interest (e.g. log export value), $C_i$ represents cohort dummies (based on the year a firm has its automation spike, $X_j$is a vector of additional controls (including sector dummies), $\delta_t$ stands for year effects, and $\epsilon_{it}$ is the error term.

The table below reports the F statistics on the null hypothesis that all cohort dummies are zero. Results are clear: the statistical significance at convectional levels is never reached. This suggests that pre-trends do not significantly differ across different treatement cohorts, which in turn makes the PTA assumption plausible for not-yet treated observations.

Table 14: Comparing different cohorts of automating firms: Estimation of Equation 4.

| D.V.: $\Delta$ in | Export value (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 |

Notes: SEs are clustered at the firm level; $F_{crit}(13, \infty)$ at the 10% significance level is 1.52.

# B Appendix: Event-study plots for different industries - Never-treated as control

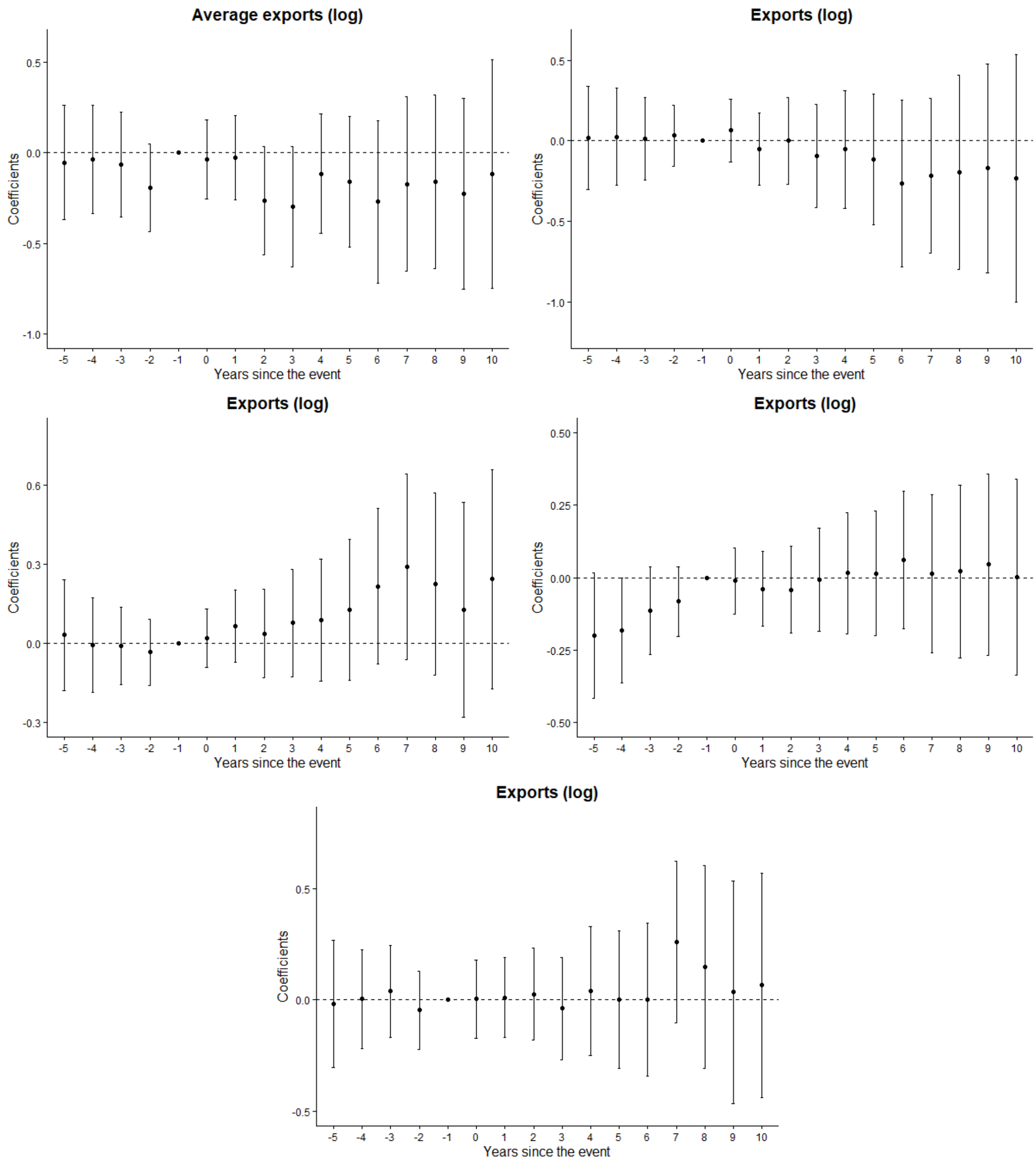


Figure 5: Export values, various estimators: Heterogeneity analysis by industry

Note: Figure plots the estimated $\beta_k$ event study coefficients from a regression of the form given in equation 2 using Callaway and Sant'Anna (2021), where the dependent variable is log total exports. The control group is not-yet treated observations. The event is defined as an automation spike. $\beta_{-1}$, the coefficient of the year prior to an automation spike of a firm, is normalized to zero. The industries include Manufacturing of food, beverage and tobacco products (divisions 10-12 of NACE Rev. 2); Wood, paper, and printing (16-18); Petroleum and chemical industry (19-23); Metal industries (24-25); Other industries (NACE 31-33).

# C Appendix: Event-study plots for different industries

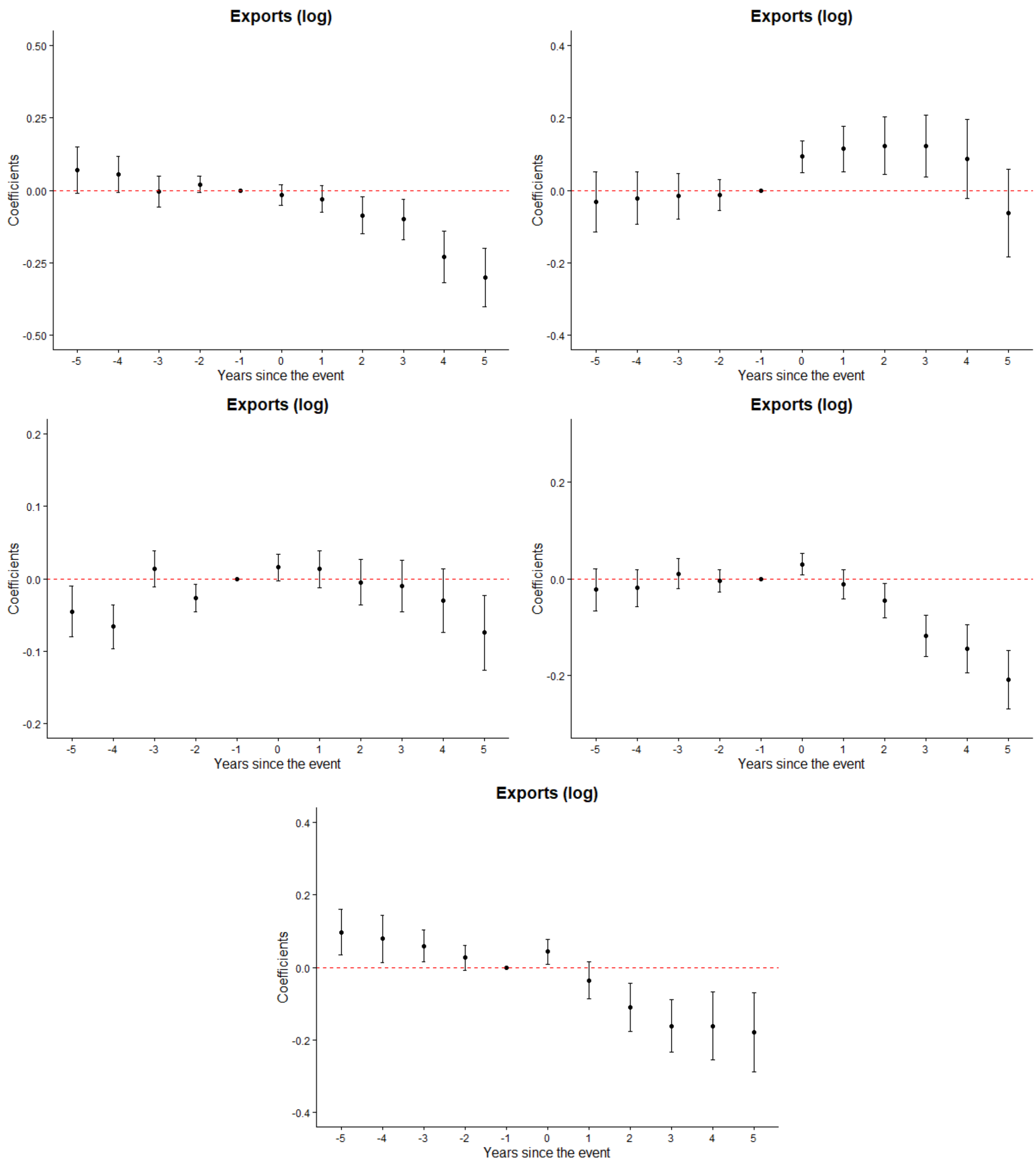


Figure 6: Export values, various estimators: Heterogeneity analysis by industry

Note: Figure plots the estimated $\beta_k$ event study coefficients from a regression of the form given in equation 2 using Callaway and Sant'Anna (2021), where the dependent variable is log total exports. The control group is not-yet treated observations. The event is defined as an automation spike. $\beta_{-1}$, the coefficient of the year prior to an automation spike of a firm, is normalized to zero. The industries include Manufacturing of food, beverage and tobacco products (divisions 10-12 of NACE Rev. 2); Wood, paper, and printing (16-18); Petroleum and chemical industry (19-23); Metal industries (24-25); Other industries (NACE 31-33).

# D Appendix: Compare with not-yet treated group, and balanced panel, and not conditioning

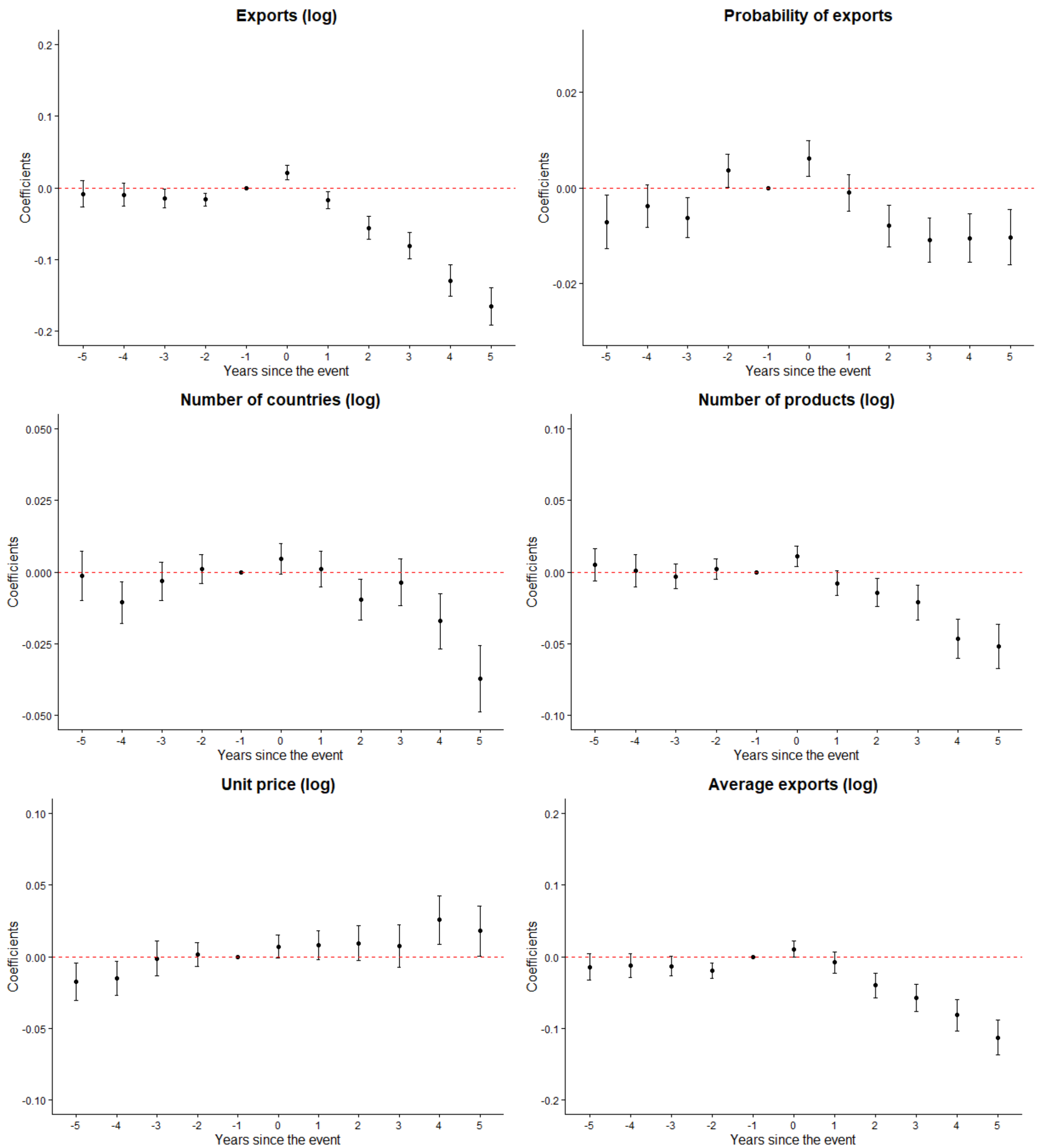


Figure 7: Various export outcomes around automation spikes (not yet treated, no controls, balanced; our original specification).

Note: Figure 9 plots the estimated $\beta_k$ event study coefficients from a regression of the form given in equation 2 using Callaway and Sant'Anna (2021), where the dependent variable is, in turn, log total exports, probability of exports, log number of countries, log number of products, log unit price, log average exports per product. The event is defined as an automation spike. The control group is not-yet treated observations. $\beta_{-1}$, the coefficient of the year prior to an automation spike of a firm, is normalized to zero. The vertical lines represent 95% confidence intervals.

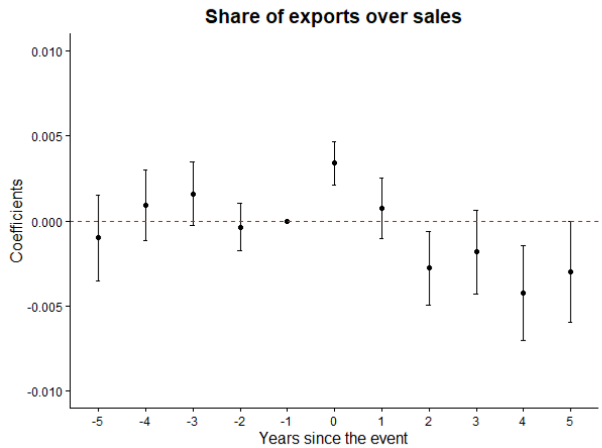


Figure 8: Share of exports over sales around automation spikes.

Note: Figure 8 plots the estimated $\beta_k$ event study coefficients from a regression of the form given in equation 2 using Callaway and Sant'Anna (2021), where the dependent variable is share of export over sales. The event is defined as an automation spike. The control group is not-yet treated observations. $\beta_{-1}$, the coefficient of the year prior to an automation spike of a firm, is normalized to zero. The vertical lines represent 95% confidence intervals.

Compare with not-yet treated group, unbalanced panel, and not conditioning

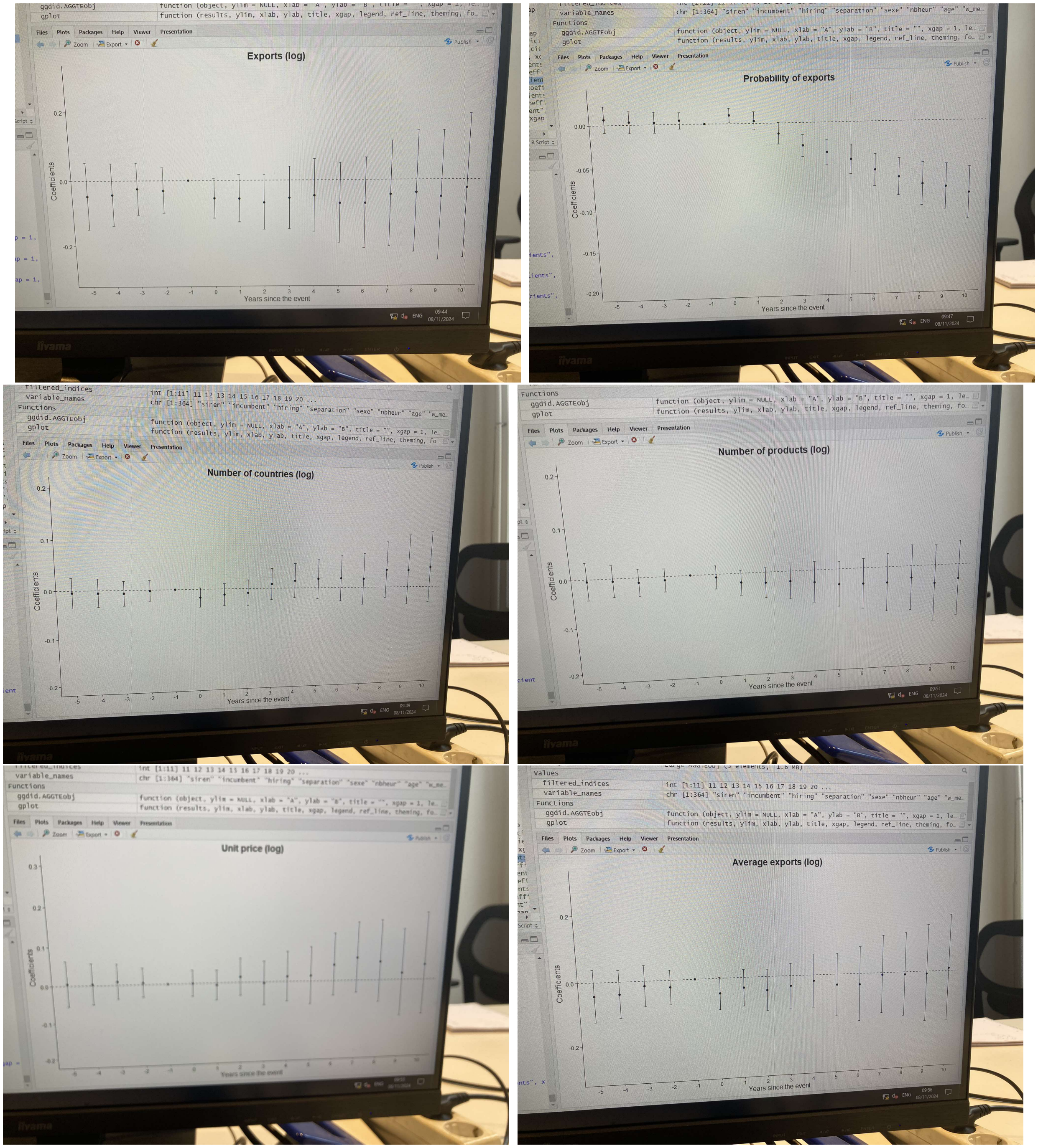


Figure 9: Various export outcomes around automation spikes.

## By size

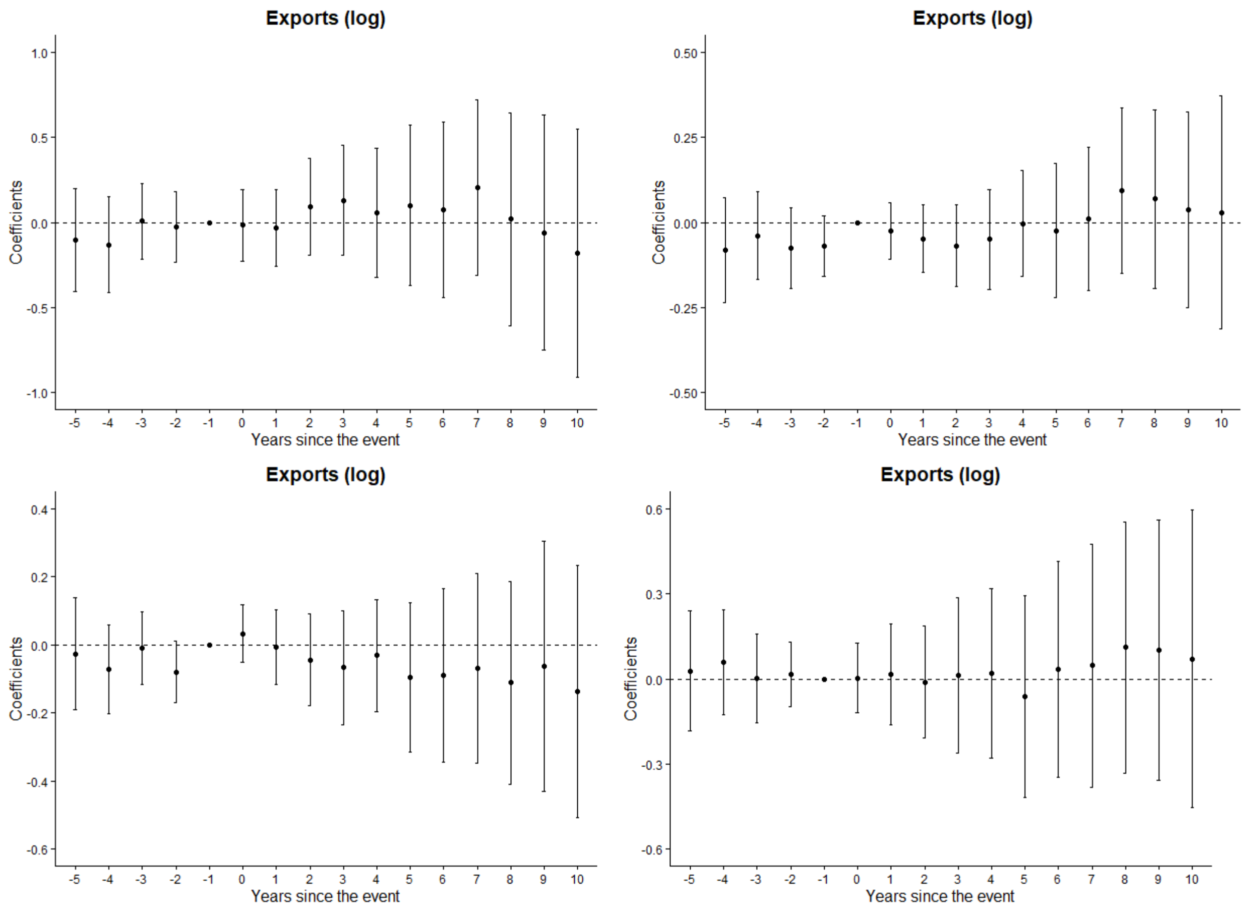


Figure 10: Log export value around automation spikes for different sizes of firms (measured before automation event)

Note: Figure 10 plots the estimated $\beta_k$ event study coefficients from a regression of the form given in equation 2 using Callaway and Sant'Anna (2021), where the dependent variable is log total exports. The event is defined as an automation spike. The control group is never treated observations. $\beta_{-1}$, the coefficient of the year prior to an automation spike of a firm, is normalized to zero. The vertical lines represent the 95% confidence intervals.Figure on the top left shows export outcomes for very small firms only, on the top right shows export outcomes for small firms only, on the bottom left shows export outcomes for medium firms only, on the bottom right shows export outcomes for big firms only.

## By industry

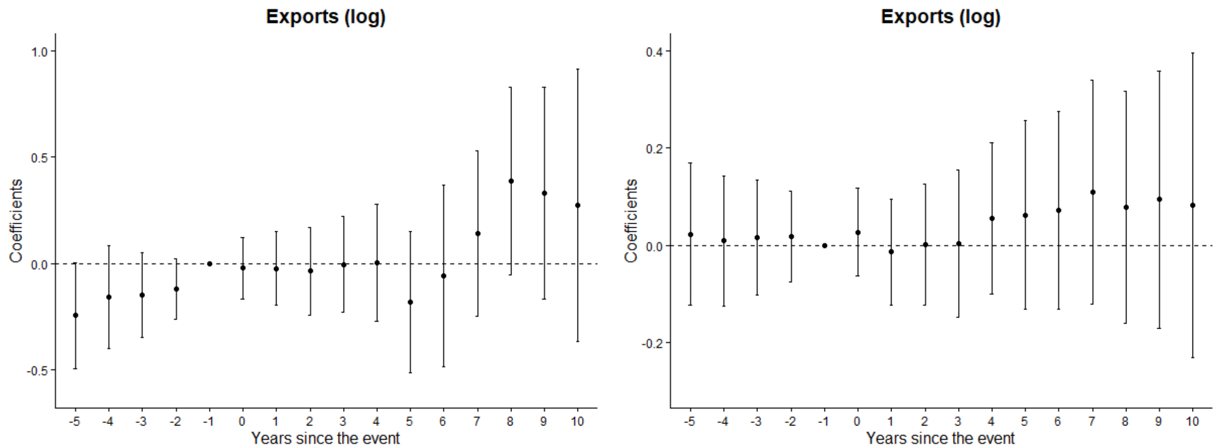


Figure 11: Log export value around automation spikes for textile industries only (left) and machinery industries only (right).

Note: Figure 11 plots the estimated $\beta_k$ event study coefficients from a regression of the form given in equation 2 using Callaway and Sant'Anna (2021), where the dependent variable is log total exports. The event is defined as an automation spike. The control group is never treated observations. $\beta_{-1}$, the coefficient of the year prior to an automation spike of a firm, is normalized to zero. The vertical lines represent the 95% confidence intervals.

## By innovating status

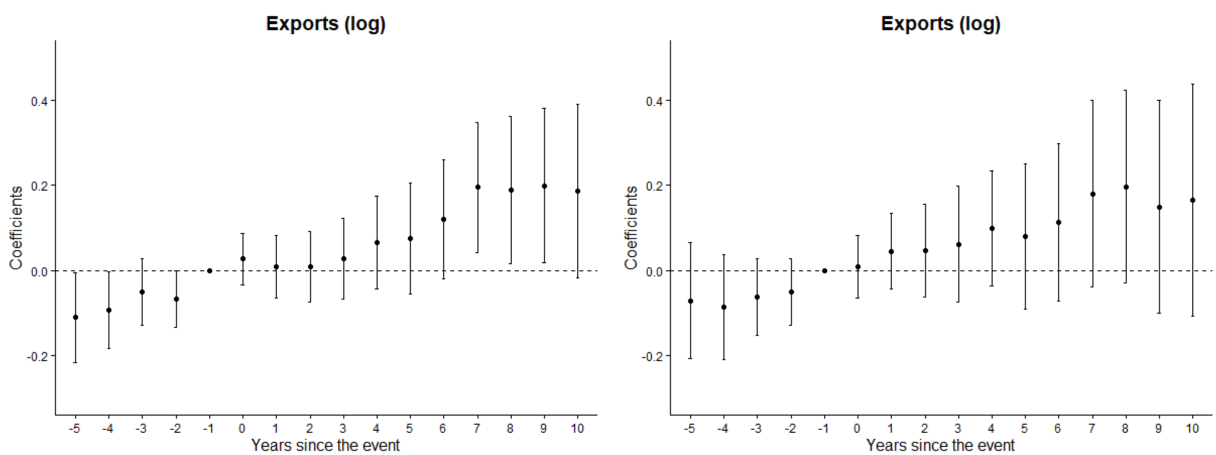


Figure 12: Log export value around automation spikes for innovators (left) and non-innovators (right)

Note: Figure 12 plots the estimated $\beta_k$ event study coefficients from a regression of the form given in equation 2 using Callaway and Sant'Anna (2021), where the dependent variable is log total exports. The event is defined as an automation spike. The control group is never treated observations. $\beta_{-1}$, the coefficient of the year prior to an automation spike of a firm, is normalized to zero. The vertical lines represent the 95% confidence intervals.

## By types of technologies

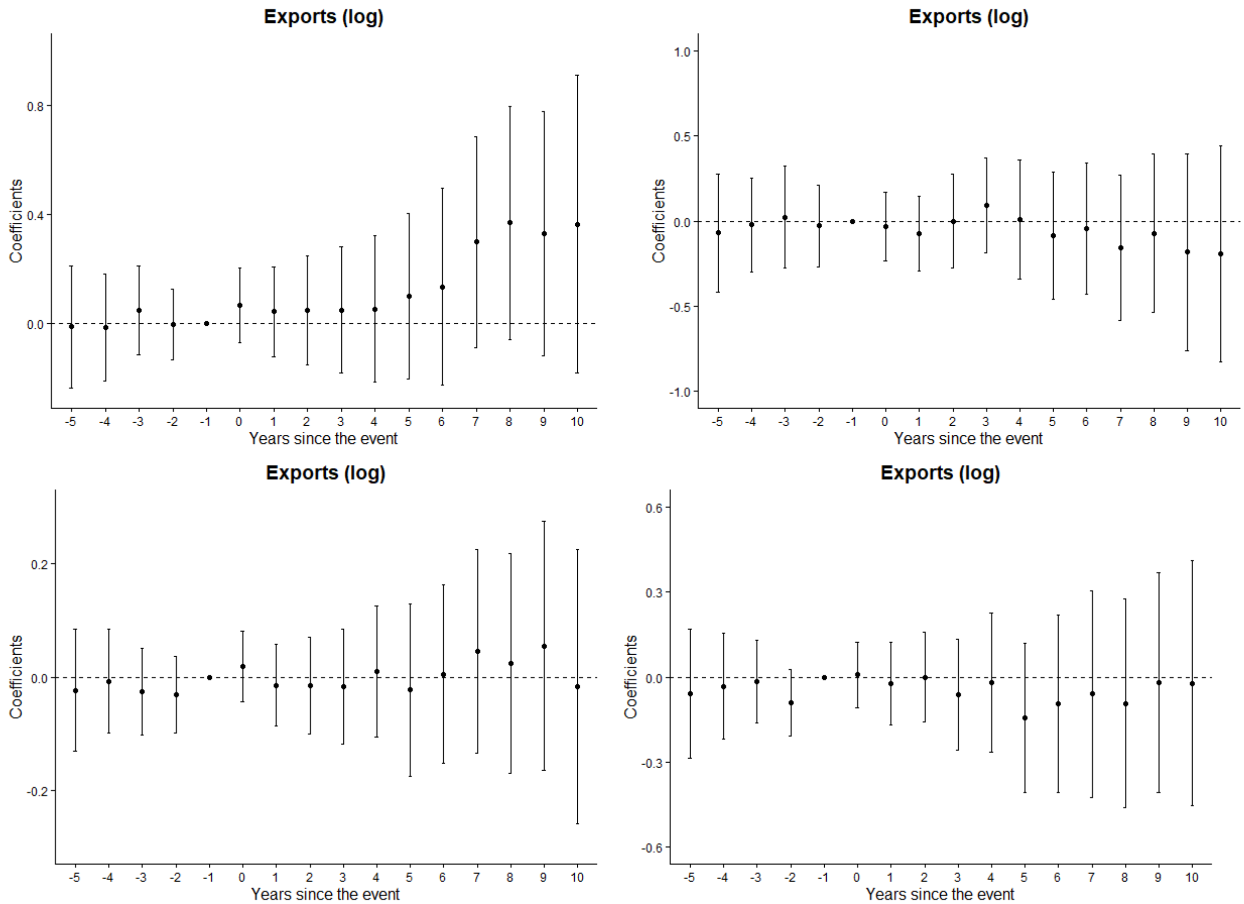


Figure 13: Log export value around spikes in specific technologies (3D printers, robots, automatic machine tools, and automatic conveyors).

Note: Figure 13 plots the estimated $\beta_k$ event study coefficients from a regression of the form given in equation 2 using Callaway and Sant'Anna (2021), where the dependent variable is log total exports. The event is defined as a spike in a specific technology (from top-left, clockwise: 3D printing, robot, automatic conveyors, automatic machine tools). The control group is never treated observations, based on each technology's specific spike. $\beta_{-1}$, the coefficient of the year prior to an automation spike of a firm, is normalized to zero. The vertical lines represent 95% confidence intervals.