Robot Adoption and Product Innovation

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Abstract

We investigate the unexplored relationship between robot technology adoption and product innovation. We exploit Spanish firm-level data on robot adoption and use a staggered timing difference-in-differences, supported by an instrumental variable approach. Instead of an enabling effect, we find a negative association between robot adoption and the probability to introduce product innovations, as well as their number. The result is particularly significant for larger, established, and non-high-tech firms. In line with industry evolution models, we rationalise and interpret the findings suggesting that a key mechanism at work in the robotisation-innovation nexus are diseconomies of scope fuelled by capacity-increasing investments. We also discuss whether industrial robots in our data feature enabling capabilities at all. Our results have important implications for understanding the role of robots in firms' operations and strategies, as well as for policy design.

Keywords: robots; automation; product innovation; diseconomies of scope; Spain

JEL Codes: O31; O33;

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1. Introduction

Historically, mechanisation of production has always been accompanied by questions about its impact on the incentive to reallocate resources, with a natural focus on the substitutability of labour (Mokyr et al. 2015). However, labour substitution is only one of the effects of automation. In this paper, we study whether the adoption of robot technology influences product innovation.

In essence, robots are capital goods, part of what has been called ‘modern manufacturing capital’ (Aghion et al. 2023). However, contemporary robots are depicted as increasingly ‘malleable’, or flexible, capital goods – multi-purpose equipment capable of executing different tasks with little re-programming. Growing robot flexibility is a clear trend, as robot technology is augmented by other technologies characterising the fourth industrial revolution (Benassi et al. 2022; Martinelli et al. 2021), both hardware (e.g., sensors, or additive manufacturing technologies) and software (e.g., artificial intelligence algorithms). Robots become a component in larger systems, such as cyber-physical systems and advanced digital production technologies (UNIDO, 2019). As such, it is possible to hypothesise that robot adoption will induce changes in firms’ behaviours that go beyond the well-known replacement and productivity effects on employment (Autor, 2019) and that are more ‘enabling’ in nature. The enabling nature of emerging technologies such as contemporary malleable robotic systems can be function of their capability to ease (or lower the costs of) experimentation of product designs, or to reduce uncertainties in the production process and to create efficiencies – thus, freeing time and capacity to feed economies of variety. This hypothesis begins to accumulate empirical support (Hirvonen et al. 2022). At the same time, most of the robots currently in use in firms are yet “the most recent iteration of industrial automation technologies that have existed for a very long time” (Fernandez-Macias et al. 2021) that continue to operate in well-bounded shop floor environments. Notwithstanding robots’ growing capabilities, the physically-constrained nature of their deployment suggests that their enabling influences on a firm’s broader decision-making structure might be limited.

Excluding robot vendors, for any other firm, robots are process technology. Hence, robot adoption might be considered a form of process innovation. From this perspective, our study is a special case of a more general theme: whether the relationship between process and product innovation is one of substitutability or synergy. At the root of process and product innovation there are different strategic considerations: process innovation is mainly driven by efficiency and cost cutting reasons; product innovation is mainly driven by the capture of value and market shares or creation(penetration) of(in) new markets (Utterback and Abernathy 1975; Klepper 1996; Damanpour and Gopalakrishnan 2001). While theoretical literature has modelled firms’ portfolio choice between product and process innovation (Lambertini 2003), the empirical evidence is still scant – even more so for the case of robotisation.

From a decision-making perspective, the impact of robot adoption on innovation can be affected by whether and how a companies’ routines change in response of the implementation of the new process technology (Gilbert 2005; Nelson and Winter 1982). On the one hand, rigid routines might limit the scope for exploration and innovation enabled by the investment in robots; on the other hand, if robot adoption imposes structural reorganisations that reverberate more generally on the firm operational structure, that might increase the chance of introducing novel products. From an economic perspective, the relationship between robot adoption and innovation depends on opportunity costs and scarcities: implementing robots is potentially a relevant financial investment (at least when accounting for investments in complementary capital and peripherals – see Benmelech and Zator 2022 and Aghion et al. 2023). This creates an allocation problem, with firms having to distribute scarce resources amongst different ends. The choice on how to address such allocation problem can affect firms’ performance at the core and persistently, as management often takes decisions on process and product innovation in the context of the development of long-term strategies. Furthermore, and possibly more important, a firm's top management might take process (including robot adoption) and product innovation decisions simultaneously, as part of an overarching and integrated market strategy (Miravete and Pernías, 2006). Simultaneous decision-making on robotisation and innovation can be shaped by many of the trade-offs we just mentioned. In an attempt to explore some of forces at play behind these strategic decisions, we look at the effect of robotisation on innovation in different firm profiles. Doing so, we try to understand potential mechanisms underlying our results.

We exploit a unique dataset of Spanish firms, coming from the Survey on Firm Strategies (*Encuesta Sobre Estrategias Empresariales*, or ESEE) and implement an event-study approach (a staggered timing difference-in-differences model) and an instrumental variable analysis to relate different indicators of product innovation to robotisation. We show that robot adoption is negatively associated to product innovation. We cannot test directly the relevance of managerial decisions on our results; therefore, we limit ourselves to offer some descriptive support. We show that there is a positive correlation between management quality and robot adoption, suggesting that our findings may, at best, underestimate the actual effect of robot adoption on product innovation. Instead, we focus on coarser economic determinants of the relationship. These are more speculative in nature, but allow us to identify some robust patterns and to relate them to general stylised facts in the evolution of industries. In particular, we explore different channels pertaining to firms' characteristics that could explain how firms' decision on product innovation and robot adoption relate. When we look at different firm profiles, we find that the negative association we detect is experienced by larger, established firms, active in sectors that are not high-tech. We interpret the findings in line with mechanisms outlined by established models of industry evolution. As industries mature (and firms grow), the incentive to allocate resources on process improvement to exploit economies of scale prevails on that of expanding variety through product innovation. By adopting robots, larger, established (features that proxy the state of a given industries life cycles) firms bet on capacity expansion – especially if responding to demand growth. Hence, robot adoption can divert resources away from product innovation, as it fuels diseconomies of scope across firm investment types. Descriptive evidence on the timing of machinery investments and product innovation seconds our insights: both tend to peak right before robot adoption, suggesting that robot technology accelerates the process of firms' focusing on capacity expansion fuelled by diseconomies of scope after the joint strategic decisions on scale of production and product innovation. Finally, we reflect on the nature of robots included in our data: these are mostly system designed to produce large quantities of few product variants (Perzylo et al. 2019); hence, rather than enabling far-reaching changes in firms' processes and routines, they are specialised tools, mostly tailored to the needs of large companies.

In summary, the paper contributes to the growing, strand of studies analysing the relationship between firm-level robot adoption and economic performance, extending the reach of automation studies from the labour market perspective to a microeconomics of innovation one. In this sense, our work builds primarily on economic reasoning and frameworks, in line with works such as Koch et al. (2021). Our unique contribution is the focus on the nexus between the adoption of industrial robots and product innovation performance. The paper is organised as follows: Section 2 provides a literature review that explores the main stylised facts of robotisation and juxtaposes three broad strands of research to construct a framework to guide the discussion of our results. Section 3 describes the data and the methodology we employ. Section 4 presents the results and Section 5 offers a discussion of the mechanisms that might be producing them. Section 6 concludes the paper.

2. Relevant Literature

The focus of our analysis is on robot technology, which is increasingly under the spotlight for its applications, and lately even for being a strategic asset (Nolan 2021). More precisely, we focus on *industrial* robots. We align with the ISO 8373 definition of industrial robot: an "automatically controlled, reprogrammable multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications".[2] Wirkiermann (2022) outlines the distinction between mechanisation (in the 19th century), computer-based automation (in the 1980s) and contemporary robotisation. The importance of robots, or telerobots (Sheridan 2016), depends on their capacity of automating routine tasks and to act as multi-purpose tools – ultimately, to generate productivity gains. Robots become an interface between humans, control software, and production activities. The decision to invest in robots answers different goals, from the reduction of operating costs to the improved resilience in facing positive or negative peaks in production, passing through an increased flexibility and a more efficient use of resources (e.g. energy). In addressing these multifaceted firms' needs, they reconfigure the very set of actions firms can engage into. As a consequence, robots might also be characterised by enabling capabilities.

Despite the interest around robot technology, economists' understanding of their technical features and patterns of adoption is yet limited. One reason for that has to do with the angle of analysis, as most of the literature on recent automation is grounded on theories of routine-biased technical change (Acemoglu and Restrepo 2019), which take occupations and job tasks as key units of analysis but lack in-depth, 'engineering' knowledge on robots as complex technology systems. A second, related reason has to do with data availability at a level granular enough to appreciate the heterogeneity of robot technology. However, recent studies are starting to draw a finer-grained picture of the implementation of robot technology into production activities. Focusing on German plant-level information, Deng et al. (2021) outline stylised facts of robot adoption, among which, the fact that robot use is relatively rare, the distribution of robots is highly skewed, and that robot adopters are 'exceptional' actors – that is, larger, with higher labour productivity, investing and exporting more and using more novel technology compared to non-robot-using plants. Benmelech and Zator (2022) confirm that robot adoption is yet limited, especially when compared to digital technologies.

We build a framework for our analysis by bridging three different strands of literature that provide relevant insights: (i) studies on firm-level automation; (ii) studies on the relationship between product and process innovation strategies; and (iii) research on the enabling effect of the adoption of emerging technologies on innovative activities.

Firm level analysis of automation and robotisation. As it is the case for more aggregate-level research, firm-level studies of automation and robotisation have focused almost exclusively on labour market impacts. Humlum (2019) uses an event-study approach (on Danish administrative data) to measure worker heterogeneity in exposure to robot adoption. Similarly, Bessen et al. (2020) and Domini et al. (2021) study automation spikes and job separation rates for Dutch and French firms, respectively. Dauth et al. (2021) measure exposure to industrial robots for Germany apportioning data from the IFR using a regional labour market approach combined with worker-level administrative data; Dottori (2021) conducts a similar exercise for Italy. As pointed out by Acemoglu et al. (2020), new firm-level

[2] This definition bounds the robots considered to those used for industrial purposes, which is our domain of interest. Furthermore, it is the definition adopted by the International Federation of Robotics (IFR). Since we use IFR data in our analysis as well, this ensures a consistent definition of the object of analysis. In the survey we use for this study (see Section 3), firms are only asked if they use "Robotics", without providing a detailed definition. However, the question on robotics excludes other technologies such as "computer-assisted design", or "numerical control machine tools" (which are alternatives firms can choose), hence the boundaries of robotics in the survey approximate the ISO definition. Furthermore, our definition is in line with the well-established work of Koch et al. (2021), who use the same data source.

analysis introduces new issues as well. In particular, the detection of a productivity effect of robots can be, in reality, the result of a selection effect: as firms adopting robots reduce production costs, they tend to gain market shares. Overall, employment gains or losses will then be a result of reallocation. In fact, when aggregating firm-level effects, the impact on total employment seems limited to composition effects, with the negative or positive impact of automation on the labour share depending on the magnitude of labour share reduction in the few, usually large, robot-adopting firms (Autor et al. 2020). Another angle of the robotisation-employment nexus is that explored by Voshaar and co-authors (2022). They find that (Spanish) robot-adopting firms exhibit greater labour cost stickiness compared to non-adopters. The result is rooted in the upskilling dynamics generated by robot adoption, and in management's reluctance to lay off robot-complementary skilled workers. These results provide further speculative support to the idea that rigidities at the decision-making level (in this case, shaped by the economic forces leading robot firms to hire skilled workers) could mediate the relationship between robotisation and innovation as well.

Exploiting more granular information, firm-level automation research began to go beyond effects on employment and to focus on the impact of robots on various indicators of performance. Kromann and Sorensen (2019) use survey data from Danish firms to relate automation measures and performance, measured as labour productivity and profit to sales ratio, finding a positive relationship. Acemoglu et al. (2020) find that French robot adopters experience an increase in value added and productivity beyond a decline in the labour share. Aghion et al. (2023) measure the impact of automation technology (captured by expenditures on industrial equipment and machines or plant-level energy consumption to proxy 'motive power') on French manufacturing firm's employment, wages, prices and profits with an event study and a shift-share setup. They find that next to a positive effect on employment, profits and sales increase while consumer prices decrease. Exploiting the same dataset we also use, Koch et al. (2021) confirm that robot adopters are exceptional in the sense that those firms that are ex ante larger, more productive and exporting have higher likelihood of adopting robots (with a higher likelihood for less skill-intensive firms). Robot adoption boosts output, TFP growth, and exporting. Alguacil et al. (2022) corroborate the findings on exporting – Spanish robot adopters increase probability, amount, and shares of export, and the technology helps in particular companies facing high export entry costs.[3] Using import data on industrial robots for French firms, Bonfiglioli et al. (2020) produce additional evidence that robot adopters differ from non-adopters ex ante, being these larger, more productive firms and employing a higher share of managers and engineers. Interestingly, they find that demand shocks lead firms both to expand (increasing employment) and automate; hence, they stress the possibility that a spurious correlation exists between automation and impact on employment. Sudekum et al. (2020) combine industry-level (IFR) data on robot adoption with firm-level information for European manufacturing to study changes in the distribution of sales, productivity, mark-ups, and profits within industries. They find that robotisation disproportionately benefits top firms, reinforcing the trend of emergence of superstar firms (Autor et al. 2020). The authors outline the possibility that robot adoption might slow down knowledge diffusion from frontier firms to laggards, or that superstar

[3] In a set of ancillary regressions aimed at looking at the mechanisms behind the effect of robotisation on exports, Alguacil et al. (2022) analyse the relation between the adoption of robots and the probability to introduce a product innovation. They find a positive and weakly significant effect. A number of factors may explain the different effect compared to our evidence. In particular, here we refer to two main issues. First, their research design, which does not account for dynamic effects, implies a rather rigid selection of 'treated firms'. In their analysis, robot adopters are firms which have adopted in time *t*, but not in previous period, making them rather intermittent robot adopters. A careful treatment of reversals is also absent. Second, the specification does not appear to be tailored to a regression with product innovation as dependent variable, lacking a proper control for the level of R&D investment.

firms could be more successful in attracting high-quality labour capable of speeding-up the implementation of the new technology.

Relationship between product and process innovation. A second strand of research that is relevant for our analysis is the economics and strategy literature on the relationship between product and process innovation or R&D activities. Traditionally, the two types of innovations have been analysed individually because of the different strategies underpinning them, which in turn answer to different internal and external stimuli: when competition is driven by high product differentiation, it is optimal to choose a product innovation strategy; when competition is mainly price driven, it is optimal to go for process innovation (Weiss 2003). Only recently, product and process innovation have been studied as strategic complements at the company level. For example, complementarities between process and product innovation are likely to emerge in the so-called process industries, where it is also more appropriate to hypothesise a relation going from process to product (Hullova et al. 2016). Theoretically and more in general, Lambertini (2003) finds that, for a monopolist, cost-reducing process R&D and product innovation are substitutes, as surplus is extracted either by reducing marginal cost for a given number of product varieties, or expanding variety for a given level of production costs. Lin (2004) contrasts this, showing that process and product R&D are negatively related only if the degree of economies of scope in process R&D is low; otherwise, cost-reducing R&D is a positive function of product variety. Mantovani (2006) finds that monopoly profits are higher when product and process strategies are jointly pursued, with initial conditions determining the share of product vs process R&D. In a dynamic setting, Lambertini and Mantovani (2009; 2010) find that process and product innovation are substitutes for a monopolist at any stage of the path towards the steady state equilibrium, and complementary in the steady state. Li and Ni (2016) identify in the learning-by-doing rate (hence, knowledge accumulation regime) for product and process innovation a key parameter deciding whether the two activities are substitutes or complements.

Studies of industry dynamics and evolution, and in particular those mapping industry life-cycles, illustrate the endogenous process leading firms to transition from a focus on product innovation to one on process innovation (Klepper 1996). The model of Klepper (1996) outlines the key mechanism behind the fact that shares of product and process R&D expenditures in an industry change over time: as production expands and profit margins decrease, firms have a growing incentive to focus on cost-reduction, rather than on the introduction of new product variants. Product innovation is mostly done by entrants, as succeeding in this activity is their only chance to compensate the scale advantage of incumbent firms. As the industry matures, the importance of scale (capacity expansion) increases, as so does, endogenously, process innovation expenditures. Bennett (2020) builds on that, and suggests that automation is pursued with higher intensity by either leading firms or laggards depending on the state of the market. In growing markets, cost-spreading incentives favours incumbents' automation; in non-growing markets, automation can be driven by market stealing incentives on the side of the laggards, which hope to gain market shares at the cost of the leading firms. Cohen and Klepper (1996a) show that the allocation of resources to process or product R&D vary with firm size: process innovation induces less direct sales growth as new processes cannot be easily sold in disembodied form compared to products. Hence, smaller growth-oriented firms will see higher return in conducting product R&D. As returns to process R&D depend on current output, firms growing larger will tend to shift to process R&D. This mechanism matches nicely our findings.

Empirically, Hirvonen et al. (2022) use text data to explore the product vs process tension by analysing the impact of advanced technology adoption in Finnish manufacturing firms. In their paper, advanced manufacturing technologies include computerised numerical control (CNC) machines, (welding) robots, laser cutters, surface-treatment technologies, measurement devices, enterprise resource planning (ERP), and computer-aided design (CAD) software. Rather than replacing workers, these technologies are adopted to boost competitive advantage; adoption of new tools lead to an expansion in product variety. These findings go in line with the expectation of an enabling capability of advanced manufacturing technologies, among which potentially robots. However, firms involved in the analysis are mostly smaller and medium enterprises that – as pointed out by Cohen and Klepper (1996a) – have 'by design' a higher incentive to engage in product innovation compared to process innovation.

Emerging technologies and innovative activities. A third piece of the framework we are building consists of literature relating the use of novel technologies and innovation behaviour. The idea that certain technologies shape the incentive to innovate in related technologies or industries is at the core of the literature on general-purpose technologies (Bresnahan and Trajtenberg 1995), in which core upstream technologies and downstream technologies that make use of the core ones have linked payoffs in R&D investments. Some technologies are what Koutrumpis et al. (2020) call 'invention machines' - what Griliches (1957) identified as 'invention of a method of inventing' (IMI) - as "they alter the playbook of innovation where they are applied" (Cockburn et al. 2019). Innovations (inventions) that spur further innovation (inventions) usually feature some elements of multi- or general-purpose, or a 'meta-technology' nature (Agrawal et al. 2019). Being multi-purpose malleable tools, robots are a good candidate for the role.

Applied literature on the impact of ICT also detected how enabling technologies open new room for actions at the firm level, resulting in higher productivity (Brynjolfsson and Hitt 2000). More recently, Brynjolfsson et al. (2021) find that a similar effect can be registered in firms adopting predictive analytics techniques. Focusing on Canadian firms, Dixon et al. (2021) find that robot adoption leads to a different type of 'innovation', namely changes in organisational structure: using robots produces a reduction in the number of managers, but an increase in the span of control for those managers that survive the change. At an even more detailed level of analysis, Furman and Teodoridis (2020) show how the automation of a research task in computer vision and motion sensing research – achieved with the introduction of the Kinect technology – impacts subsequent research productivity and type of research output, increasing the production of new ideas as well as their diversity.

Closer to the focus of our analysis, Liu et al. (2020) relate the number of industrial robots (which they use to proxy artificial intelligence) and technological innovation at the industry level, using Chinese panel data for the manufacturing sector. The authors find a positive relationship between robots and innovation (measured as patents count). However, the aggregate level of analysis as well as the size of the sample used do not permit to identify clearly and in a fine-grained manner the channels and mechanisms relating technology and performance. Niebel et al. (2019) observe the relationship between use of big data analytics and product innovation at the firm level, for a sample of manufacturing and service companies from the German ZEW ICT survey and Community Innovation Survey. By reducing uncertainty and supporting decision-making with high-quality information, the expectation is that big data analytics would help innovative activities. The authors find that the use of these techniques raises both the propensity to innovate as well as innovation intensity (measured as the share of sales from new products and services).

The enabling capability of an emerging technology more narrowly defined is studied in Rammer et al. (2022) and Babina et al (2023), who focus on artificial intelligence (AI). Rammer et al. (2022) use the 2018 module of the German section of the Community Innovation Survey to study the relationship between the use of AI in firms and product and process innovation. While AI is used by a very small share of firms, those adopting AI (and, in particular, the firms that contribute with in-house efforts to the development of AI solutions) use it to innovate, especially product innovations that are new to the market. The analysis is limited by the cross-section nature of the data, but it is useful to shed light on the fact that only certain specific technologies have enabling capabilities. Babina et al. (2023) exploit resume and job posting data to test the hypothesis that AI adoption (via hiring of AI skills) lowers the cost of new product development. Orthogonal to robot technology, in their study AI adoption does not impact process innovation (and, thus, labour replacement and productivity); rather it, shows an enabling effect as discussed in this paper: AI shortens experimentation time and enables product variety thanks to better predictions of demand.

Taking stock of the literature. In summary, linking three strands of literature we have at hand a rich picture of the profile of robot adopters, as well as of the impacts following the adoption of robot technology. First, firm-level studies of automation and robotisation find evidence of self-sorting: adopters are already better performing firms before automation, and automation provides a further boost to performance. Second, whether robots are used only as a process technology or also with the goal of upgrading product offering depends on the forces set in motion by robotisation inside the firm (e.g. learning) and the concurrent strategic decisions taken by management, e.g. adjustment of production or changes in market positioning. Third, the enabling capability of a technology might depend on its very technical features: software technologies such as AI or advanced ICTs such as predictive analytics can be used as a supporting tool to reduce uncertainty and to guide innovation resource allocation decisions. It remains to be seen whether industrial robots are characterised by the same features that make emerging software technologies enabling. Taken all together, and given its malleability, it cannot be excluded that robot technology might help to experiment with new product designs and prototypes; however, this capability might be a feature of a subset of robots only, or one that companies are not able or willing to exploit fully.

3. Data and Empirical Strategy

Our analysis covers the period 1991-2016, a period during which there have been significant transformations in the production processes of firms worldwide. Industrial robots played an important part in these changes. Acemoglu and Restrepo (2020) provide evidence of a fourfold rise in the stock of (industrial) robots in the United States and western Europe between 1993 and 2007, while Graetz and Michaels (2018) show the dramatic fall in robot prices, which halved (and decreased even more when quality-adjusted) roughly in the same period for a sample of six advanced economies.

The adoption of robots has been quite heterogeneous among countries in the last decades (OECD, 2019). Spain, which, according to the World Robotics 2022 Report[4], is still among the first twenty countries worldwide in terms of robot density (number of robots per 10,000 employees), has a specific trend in robotisation. Notably, it has experienced a surge of operational robots' adoption by a factor of five in the period 1993-2000, mostly due to the large diffusion of automation in the automotive industry.

For our analysis, we mainly draw on longitudinal firm-level data from a survey of Spanish manufacturing companies: the *Encuesta Sobre Estrategias Empresariales* (ESEE, Survey on Firm Strategies). ESEE is a survey carried out annually by the SEPI Foundation[5] and comprising nearly 2,000 Spanish manufacturing companies. Previous studies have highlighted how ESEE data cover approximately 22% of total Spanish employment in manufacturing and that it includes the full population of manufacturing firms with more than 200 employees and a representative sample of SMEs between 10 and 200 employees (Barrios et al. 2003; D'Agostino and Moreno 2019). ESEE has been extensively employed as a data source for applied studies in economics and management at the firm level.[6]

[4] https://ifr.org/ifr-press-releases/news/china-overtakes-usa-in-robot-density (last accessed 7 December 2023)
[5] https://www.fundacionsepi.es/investigacion/esee/en/spresentacion.asp (last accessed 7 December 2023)
[6] For a list of publications see https://www.fundacionsepi.es/investigacion/esee/en/sesee_articulos.asp (last accessed 7 December 2023)

The ESEE questionnaire includes information on a wide range of topics, such as market and product characteristics, financial data and production activities. For the purpose of our research, ESEE data is ideal because it contains: (i) information on the adoption of industrial robots for firm day-to-day production activities; and (ii) information on firm's product innovation activities. Several variables within ESEE data, like the one capturing robotisation on which we shall return, are collected every four years and refer to the previous three/four-year period. Our final sample entails 3,304 firms over a rather long time-span, made of seven relevant periods between 1991 and 2016 (1991-1993, 1994-1997, 1998-2001, 2002-2005, 2006-2009, 2010-2013, and 2014-2016).

Our empirical approach draws on Koch et al. (2021), which directly accounts for the systematic differences between robot adopters and non-adopters. Indeed, relevant differences exist between the two groups of firms. Table 1 reports some descriptive statistics on this aspect. As expected, differences are relevant and always statistically significant. Similar to what has been identified in the literature (Deng et al. 2021), the crude difference between adopters and non-adopters reveals that the former tend to innovate more in products, are larger, invest more in machinery and R&D and are more internationalised.

Given these systematic differences,[7] we adopt a staggered timing difference-in-differences (DiD) approach, which allows to capture the effect of a treatment (i.e. robotisation) that may happen in different points in time.

$$ProductInnovation_{it} = \alpha_i + \tau_t + \sum_{p=-5}^{-2} \beta_p Robot_{it}^p + \sum_{p=0}^{2} \beta_p Robot_{it}^p + X_{it}\varphi + \sum_j \sum_t \sigma_{jt} Ind_j * \tau_t + \varepsilon_{it}$$

where $Robot_{it}^p = 1[t - C_i = p]$ is an indicator for robot adopting firm i in cohort C_i (the period of treatment) being p periods from the first adoption. β_p are the main parameters of interest and measure the robotisation effect on product innovation relative to one period before first adoption.[8] The variable capturing robotisation is available from 1991 and covers a 4-year period. As our focus is on companies switching to robot adoption, we follow Koch et al. (2021) and retain only companies which report not having adopted robots in the first period of observation (1991-1993).[9] Initially, we assume the absence of reversals, i.e. once robot technologies are adopted firms keep their treated status. It is worth noting that the inclusion of pre-treatment variables allows us to uncover potential anticipation effects of robotisation, and is the starting point to assess the fulfilment of the parallel trend assumption.

Product innovation is captured in two ways throughout our empirical analysis. These are in line with the measures employed by a large part of the literature and available from the Community Innovation Survey (CIS) (e.g. Ballot et al. 2015; Frenz and Prevezer 2012). Respondent firms were asked whether they introduced new (or significantly improved) product innovations and the number of these product innovations. We make use of two variables. The first focuses on the *probability* of introducing a product innovation. This is captured by a dummy variable taking value one if this happened at least once during the relevant period, and zero otherwise. In this case, our estimation

[7] Given these differences between adopters and non-adopters in a set of unreported regressions, whose results remain available upon request, we drop firms that never adopted robots, to focus on a more homogeneous group of companies. Results confirm our baseline evidence presented in Section 4.1.
[8] More precisely, β_p measure the difference in product innovation between robot adopting and non-adopting firms p periods from first adoption (before and after), relative to the outcome differences between adopting and non – adopting firms in the excluded periods (one period before adoption).
[9] We drop a total of 1,041 unique companies from our sample.

amounts to a linear probability model. The second variable captures the *number* of product innovations. This is measured as the average number of product innovations over each period. Given the highly skewed nature of the variable, we employ its naturally log-transformed value.

In Equation 1, we include a vector of X_{it} time-varying characteristics of the firm that can affect product innovation performance and may be associated with the decision to adopt robot technologies. The inclusion of this vector allows controlling for omitted variable bias driven by observables. More in details, we control for a set of firm-level characteristics including firm size, measured as the average number of full-time equivalent employees in the relevant four-year period. We also include two measures of investment. First, we measure the total expenditure in R&D as the sum of intra- and extra-mural expenditures in the period. Second, we include the investment in industrial machinery. Both measures have been deflated by using the industry-level consumer price index provided by the Spanish statistical office (*Instituto Nacional de Estadística*) (with 2015 as base year). In addition, we control for the share of foreign ownership (both as direct and indirect foreign capital participation) over the relevant time period. We also account for the exposure of the firm to international markets by including the share of the total value of exports over sales in the relevant period. All the controls have been lagged by one year to mitigate reverse causality problems and have been transformed in natural logarithms. We also introduced a set of period fixed effects τ_t controlling for time varying shocks which can jointly affect the firms in our sample (e.g. business cycle effects). The coefficient α_i captures the time invariant firm heterogeneity that may be associated to both automation and innovation performance and is generated also by unobservable factors, like managerial orientation and baseline productivity.[10] Finally, to control for sector specific time varying shocks we include the interaction between industry and time dummies ($Ind_j * \tau_t$).[11] We also test for the parallel trend assumption by checking whether the lead variables are not different from zero (our H_0). If we fail to reject the null hypothesis, this would suggest that before the treatment the adopter and the non-adopters were subject to common trends conditional on observable and unobservable characteristics.

Static and dynamic treatment effect estimates adopting staggered timing DiD approaches such as that employed in our work may be affected by significant biases (Goodman-Bacon 2021). Notably, Sun and Abraham (2021) show that dynamic treatment estimates are biased when there is variation in treatment timing and treatment effect heterogeneity, which in our case could be due to the likely differences in the capabilities of robot technologies, which have certainly been improving along a learning curve throughout the period we consider. Additional complications can be posed by the presence of reversals: firms that during the full period of observation switch in and out of treatment. While this circumstance should not be too common when robotisation implies large organisational changes and initial fixed costs, we cannot exclude that firms opt out from robotisation – e.g. due to inferior performances, compared to expectations.

We implement a series of checks to make sure that our results are robust to these issues. Regarding the first point, we follow Callaway and Sant'Anna (2021) who propose an approach which first estimates the individual cohort-time-specific treatment effects, thus allowing for treatment effect heterogeneity, and then aggregates all the possible 2 X 2 comparisons to produce measures of the overall (properly weighted) treatment effects. As far as the second issue is concerned, we rely on the estimator

[10] Given the relatively long time period we consider in our analysis, the assumption of time invariance of the unobserved heterogeneity component may be far-fetched. In a set of unreported regression – which remain available upon request – we have run our analysis on four shorter time periods covering three (4-year long) waves of the ESEE panel each (1991-2002; 1994-2006; 1998-2010; 2002-2014). Results yield the same conclusions of the baseline evidence presented in Section 4.1.

[11] Industries are defined at the NACE (rev. 2) 2-digit code level. Notably, we use the aggregated version of industrial classification provided in ESEE data (20 manufacturing industries overall). Please see https://www.fundacionsepi.es/investigacion/esee/en/svariables/disponibles.asp.

proposed by de Chaisemartin and D'Haultfoeuille (2022). The authors develop an approach for estimating treatment effects under treatment timing variation and treatment effect heterogeneity under more general settings, where treatments may be reversible.

4. Results

4.1 The relation between robotisation and product innovation

Our baseline evidence rests on the results emerging from the staggered timing DiD model, discussed in Section 3. We rely on these estimates to provide an account of whether there is an association between robot adoption and the propensity to introduce a new product or the number of new products introduced by the firm. These results are reported, respectively, in Column 1 and 2 of Table 2.

Before proceeding, it is important to consider how we verify the plausibility of the parallel trend assumption. In general, we follow recent studies (Roth 2022; Deryugina 2017) to examine the (joint) significance of the β_p coefficients, which capture the differences between adopters and non-adopters before the actual adoption takes place. Surely, individual pre-treatment coefficients can reveal milder violations of the assumption. Nevertheless, we conduct an additional robustness exercise, using the approach proposed by Roth (2022)[12], which checks the stability of the evidence in the presence of a violation of the pre-trend assumption.[13] For the sake of completeness and transparency, in Table A 1 we report, for each regression in our study, the number of pre-treatment coefficients significant at the 95% level, the joint significance of pre-treatment coefficients and the value of the likelihood ratio proposed by Roth (2022). A ratio below 1 signals a lower probability of obtaining the coefficients under the chosen pre-trend compared to a parallel trend, so it signals the plausibility of the parallel trend assumption. To anticipate an important element related to the robustness of our results, one can notice how, even when there are signs of violation of the parallel trend assumption based on the significance of the pre-treatment coefficients, the likelihood ratio based on Roth (2022) always supports the credibility of our evidence.

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[12] Roth (2022) provides evidence that pre-trend testing is statistically under-powered and that conditioning the estimation of a treatment effect on passing a pre-trends test can actually lead to estimation bias. His approach allows researchers to check the sensitivity of results to plausible violations based on a hypothesised trend. We implement this method to examine the sensitivity of our estimates to potential violations of the parallel trend assumption.

[13] This is the ratio of the likelihood of observing the coefficients from the estimates conditional on having a hypothesised pre-trend over the likelihood of observing them under parallel trends. This indicates how much less likely are the observed coefficients under the hypothesised pre-trend compared to under parallel trend. A ratio below 1 signals a lower probability of obtaining the coefficients under the chosen pre-trend compared to a parallel trend, so it signals the plausibility of the parallel trend assumption. In the absence of theoretical expectations on the shape of the trend, we employed the trend that best mimics the coefficients plot, which is a nonlinear quadratic trend (inverted U-shape). We further corroborate the robustness of the results from the Roth test, by checking the sensitivity of the test results to different functional forms and different power levels of the test. For the two specifications for the baseline regression model (Table 2), we computed the value of the Roth likelihood test for power levels from 30% to 90% in increments of 10 percentage points. The power level of the Roth test is the probability one would find a significant pre-trend under the hypothesised pre-trend. For example, in the linear trend case the lower the power level the flatter is the trend line, so there is a low probability of pre-trend but also higher probability of no significant effect in case the hypothesised trend is true. For each of the two models Figure A1 reports the value of the likelihood test against the respective power level for each hypothesised trend. The trends are: 1) linear; 2) quadratic; 3) cubic; 4) quadratic polynomial I ($y = -bx^2 + bx$) quadratic polynomial II ($y = -bx^2 - bx$). Figure A1 plots the results: no matter what shape or power level we assume, the Roth test is always below the cut-off point of 1, thus supporting our results.

Figure 1 provides a graphical representation of the treatment coefficients from Table 2: pre-treatment coefficients are neither on an upward or downward trend prior to first adoption, supporting the assumption that treated and control groups are on parallel trends prior to treatment. The p-values associated to the joint significance of the pre-treatment coefficients (0.171 and 0.146, respectively) provide support to the implementation of our approach. In relation to the actual effect of robotisation on product innovation, our results point to a negative effect which persists after two periods (8 years) from the actual adoption; this is noticeable for both the propensity and the number of product innovations.[14] The magnitude of the effect ranges from -5.2 to -14.4 percentage points in the case of the effect on the propensity and from -9.4% to -13.8% in the case of the effect on the number of new products introduced by the firm on the market.[15]

We check the robustness of this evidence. We envisage two problems associated to our baseline results. First, our estimates would be biased in presence of variation in treatment timing and treatment effect heterogeneity (e.g. Sun and Abraham 2021). In our case, firms can adopt robots at different points in time and this can possibly involve different cohorts of robots, with different capabilities. Second, a bias may emerge due to the presence of reversals (e.g. de Chaisemartin and D'Haultfoeuille 2022): that is, at some point firms may decide to opt-out from robotisation. For the first point we resort to the estimator proposed by Callaway and Sant'Anna (2021), while for the problem related to the presence of reversals, we rely on the estimator proposed by de Chaisemartin and D'Haultfoeuille (2022). Results for Callaway and Sant'Anna (2021) and de Chaisemartin and D'Haultfoeuille (2022) estimators are shown in Figure 2 and Figure 3 respectively.

As far as the former is concerned, we can graphically notice the absence of clearly ascending or descending trends before the adoption. In addition, the use of this technique is corroborated by the fact that the average pre-treatment coefficients are non-significant (with p-values of 0.229 and 0.442 respectively) for both the estimations, which are focusing on the probability and the number of new products. The emerging evidence supports the presence of a negative effect of robotisation on product innovations that persists up to 8 years after the adoption. In the case of the results concerning the probability of product innovation, we notice that the coefficient of the effect at the year of adoption, while being negative is marginally not significant (p-value 0.111).

When we implement the estimation proposed by de Chaisemartin and D'Haultfoeuille (2022), we still confirm the negative effect of robotisation and the fact that this tends to persist even after the adoption. Although we notice a mild violation of the parallel trend assumption, we still notice an effect that is negative and persistent up to 2 periods (8 years) after the adoption.[16]

The validity of our staggered DiD estimation hinges on the parallel trend assumption. To further support the credibility of our main result, we employ a different econometric approach based on the use of an instrumental variable, which is not subject to this assumption.[17] Our instrumenting approach relies

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[14] We cannot exclude the presence of an anticipation effect given the significance of the coefficient at p=-2. However, the global test of joint significance of pre-treatment coefficients as well as the likelihood ratio test based on Roth (2022) and the sensitivity analysis we perform (see Table A1 and Figure A1) support the credibility of our evidence vis a vis the parallel trend assumption.

[15] In a set of unreported regressions – which remain available upon request – we have considered whether this effect depends on the type of product innovation introduced. That is, we looked at the probability to introduce new products associated to new materials, new components and new functions. Results show that it is the probability to introduce new components which is mainly driving the result on the overall probability to introduce innovation; the negative the effect of robotisation on the probability to introduce new materials and new functions materialises two periods after adoption.

[16] In the case of the effect on the number of innovations, the effect of the 1-period lagged treatment, albeit negative, is not significant, unlike the effect after 2 periods (i.e. up to 8 years).

[17] Such an approach turns out to provide robustness to our evidence also in light of the possible simultaneity in the focal firm's decisions regarding innovation and robotisation. We would like to thank one of the referees for pointing this out.

on the adoption of robots in the same sector of the focal firm, but in export destination countries. The instrument is built as follows. We take the number of operating robots in EU and OECD countries in the same industry of the focal firm and we weight it by the firm's export intensity to EU and OECD markets (i.e. the share of export to these destination countries over the total revenues). Our identification strategy rests on the following intuition. The adoption of robots by competitors in the export destination countries signals the availability of robot technologies that are suitable for the industrial applications in a given sector. Moreover, it should trigger the adoption of robots by the focal firm, which attempts to stay competitive on its destination markets. Foreign adoption is expected to affect product innovativeness, only through the consequent decision of the focal firm to robotise (or not). Table 3 shows the results of our estimation, we allow one lag (i.e. 4 years) to occur between robot adoption and product innovation. [18] Columns 1 and 2 reports the results of a benchmark OLS fixed effect (FE) regressions, while Columns 3, 4 and 5 refer to IV estimates. At the outset we should notice that the first stage estimates provide reassuring confirmation that the instrument is not weak, given the values of the Kleibergen-Paap F. When comparing FE and IV coefficients the latter seem to be greater in absolute value, meaning that IV corrects for an upward bias, which is expected, due to the already discussed selection of firms into robotisation as well as potential unobservables that may jointly shape robotisation and innovation strategies. Hence, we confirm the negative effect that robotisation seem to have on both the indicators we use to capture product innovation. Our identification strategy may suffer from endogeneity in case foreign adoption of robots is driven by the focal firm's one. This could happen when the focal firm can exert a market power in the foreign markets that is large enough to shape the foreign competitors' behaviour. To account for this, we exclude from our analysis top exporters (1% and 10% respectively). Results are shown in Table 4 and confirm our evidence on the negative effect of robotisation on product innovation.[19]

Our IV could potentially account for simultaneity in the decision to robotise and innovate; however, due to lack of data we are unable to directly control for the omission of managerial choices which could affect both the outcome and treatment variables. While the literature shows that managers' styles tend to be quite sticky (Bertrand and Schoar 2003), possible variations in the firm strategies brought about by a company change in management is something we cannot control for. Instead, we can provide some discussion looking at how management quality relates to innovation, on the one hand, and robotisation, on the other. Extant evidence suggests the presence of a positive relation between management quality and firm performance, both in terms of productivity and innovation (see among others Arvanitis et al. 2016; Bloom et al. 2013; Beugelsdijk 2008; Schneebacher et al. 2021). As far as the relation with robots, the literature is scant. By adopting an exploratory approach, we conducted a descriptive analysis on the basis of the data coming from the World Management Survey (WMS; Bloom et al. 2021)[20] to verify the existence of such positive link between 'good management' and robot adoption for Spain. We employed IFR sectoral data combined with WMS data. A correlational analysis shows that a positive association between management quality and robotisation does exist (ρ=0.448, t-stat=7.299). Based on the above, we deem that, if anything, our estimates would be upward biased (less negative), leaving unaltered our evidence on the negative influence of robotisation on innovation. This

[18] In a set of unreported (but available upon request) regressions we re-run the same IV estimates with a different lag structure. While using no lags, the instrument turns weak (F is lower than 10) hampering any credible evidence. When using 2 lags, the emerging evidence is in line with the IV estimates we report here: negative effects are found, albeit non-significant for the probability of product innovation.

[19] Our identification strategy may be challenged also by possible productivity shocks that affect export (which is one of the element of our instrument) and the decision to innovate. In a set of unreported (but available upon request) estimations we made sure that the stability of the results does not suffer from the inclusion of productivity as a control.

[20] https://worldmanagementsurvey.org/ (last accessed 7 December 2023).

evidence constitutes only a primer: more robust controls should come from more suitable firm-level data on strategic decisions, which we are unable to deploy in this study.

4.2 Heterogeneity and channels

Given the baseline evidence, we now provide a tentative exploration of the economic channels that could help explain the relation between robotisation and innovation.

Firm size. We first consider whether size plays a role. We start with the link between robot adoption and innovation, once again captured by the propensity (**Error! Reference source not found.**) and the number of product innovations (**Error! Reference source not found.**). While the p-value of the joint significance of the treatment parameters casts doubts on the capacity to meet the parallel trend assumption for medium-sized firms (Column 2 of **Error! Reference source not found.**), these doubts are relaxed by the likelihood ratio derived from Roth (2022) (see Table *A 1*). We also observe that it is specifically large companies that are characterised by a negative association between robotisation and the probability of introducing a new product (Column 3 of **Error! Reference source not found.**). As in the baseline regression, this effect persists after the treatment (up to 8 years after). For small firms such an effect is not found (Column 1 of **Error! Reference source not found.**). A similar evidence, without any concern regarding the parallel trend assumption for medium-sized firms, can be found when considering the effect on the number of new products introduced by the company (**Error! Reference source not found.**). All in all, the negative and persistent effect is found for large companies.

Firm age. We also consider what is the role played by firm age[21], in order to ascertain whether the tension between robotisation and innovativeness unfolds in young or established firms. Once again, we distinguish between the two main innovative outcomes: the propensity (**Error! Reference source not found.**) and the number of product innovations (**Error! Reference source not found.**). Quite consistently, the persistent negative effect is mainly traceable among established companies. Mid-age and old firms experience a negative and persistent association between robot adoption and the probability to introduce product innovations, while mid-age firms display also a persistent reduction in the magnitude of product innovation.

Sector. Finally, in Table 9, we look at whether it is the sector in which the firm operates that determines the relationship between robot adoption and innovation We find that firms operating in high-tech sectors (Column 3) face a more tenuous tension between robotisation and propensity to introduce a new product than firms operating in mid- (Column 2) and low-tech sectors (Column 1).[22] In fact, the negative and lagged effect seems to characterise in particular low-tech industries, albeit a violation of the parallel trend assumption would call for caution. A similar effect emerges for the number of product innovation; no persistent negative effect is found for high-tech companies (Column 6), and a mild negative effect characterise mid-tech sectors (Column 5). Once again, despite the possible violation of the parallel trend assumption, low tech sectors (Column 4) seem to be characterised by a clearly negative and persistent effect of robot adoption. However, it is important to stress that notwithstanding the traces of violations in the parallel trend assumption, the value of the likelihood ratios following Roth (2022) (see Table A1) supports the robustness of the results just presented. To capture additional nuances of this channel, we

[21] In a set of unreported regressions, which remain available upon request, we consider whether the inclusion of age as an additional control affect our estimates. Results are very much aligned with the baseline evidence reported in Section 4.1.

[22] Industry classification follows OECD (2016) and aggregates medium-high tech and medium-low tech due to the low number of cases.

separate firms operating in robot intensive vs non robot intensive industries. We rely on IFR data and define non-robot intensive (robot intensive) industries as those where the operational stock of industrial robots is below (above) the world median. Table 10 shows the results for our outcome variables (the probability and the number of product innovations) for the two sub-samples: firms operating in robot intensive industries (Columns 1 and 3) and firms operating in non-robot intensive industries (Columns 2 and 4). We find that the tension between innovation and robotisation is much less severe in the case of robot-intensive sectors. While we observe a possible violation of the parallel trend assumption for non-robot intensive industries when employing the probability of innovation as dependent variable, again the ratio proposed by Roth (2022) supports our evidence.

5. Discussion

We explore some arguments that can help us rationalise our findings. These insights are of speculative nature, but aim at connecting our findings with more general mechanisms at work in the interplay between process and product innovation, as well as to guide further analysis.

Robot adoption influences the process-product innovation trade-off. Robotisation and product innovation might be processes that respond to different strategic logics and incentives within a firm. A product innovation strategy responds economies of variety and to the logic of value creation and capture, while robotisation, as process innovation, aims at cost reduction and can be justified by cost-spreading incentives (Cohen and Klepper 1996b). Robot adoption can be seen as an instantiation of localised technical change (Atkinson and Stiglitz 1969): hence, its role might be confined to the organisation of operations along the production process (Hopp and Spearman 2011) without spilling over to or influencing other firm activities. In this case, even in absence of a trade-off, robots might not induce any enabling effect beyond their limited domain of use.

While being related to different strategic levers, the two activities might compete for the same pool of resources inside a firm. Given this allocation problem, a company will likely take decisions on robotisation and product innovation simultaneously, as part of a broader strategy for the medium- and long-term. This can turn product and process innovation decisions into complement or substitutes, depending on the nature of their interdependence (Miravete and Pernias 2006). If there exist supermodularity in firms' strategies, more process innovation could, theoretically, lead to more product innovation – precisely the enabling effect expected by a part of the literature on robot technology. However, in our baseline analysis, only a negative (and persistent) relationship between robotisation and product innovation emerges. This indicates that robotisation and product innovation are substitutes. Substitutability might depend on the fact that, given limited (financial, managerial, time) resources, firms face an allocation problem choosing between two alternative strategies, namely whether to purchase and implement robots, or to develop new or improved products. Alternatively, substitutability can emerge if a firm's long-term strategic decision such as that on the intensity of product innovation is rebalanced given the impact of process technology (here, robots) on production. In this context, two mechanisms can be relevant to shape a firm's decision-making. The first is knowledge-based: as robot technology is not 'plug-and-play', adoption might require organisational adjustments, routines' updating, and the formation of specific – technical, planning, and managerial – capabilities, which might increase returns to accumulation of equipment-specific knowledge and imply dis-investments from product-innovation-related activities. The re-direction of a firm's focus (investment) might potentially occur via flows of labour. On the one hand, the decrease of labour costs for the factory floor due to robotisation could make room for expanding employment in high-skills functions, including the design and prototyping of new products. On the other hand, the outflow of labour might include workers employed in different, non-overlapping activities, including some involved in product innovation. This will happen when the task vector composing some occupations features indivisibilities – that is, activities related to both process and product innovation. In this case, the outflow of talent induced by the adoption of process technology might spill over to loss of talent in product-related tasks: robotisation might improve firms' exploitation capabilities (better processes) while de-skilling them with respect to exploration (new ideas and designs) capabilities. Unfortunately, our data does not allow us to check for this particular channel. All in all, this first dynamics fits with what is suggested in the model by Li and Ni (2016), where the two activities become substitutes if the rate of knowledge accumulation is higher for process innovation – in our case, after robot adoption. In a nutshell, the take home message is that higher marginal returns in fine-tuning robots steer away efforts from product innovation.

A second mechanism is that illustrated by the received literature on industry evolution (Klepper 1996; 2015). While transitioning from birth to maturity, an industry will increase the resources allocated to process innovation and decrease those spent to introduce new products. The reason for that stands in the endogenous interplay between the incentives faced by entrants and incumbents. New firms need to produce (relatively) more product innovation to extract a margin from the market price; (surviving) established producers expand capacity in their competition for the market and, therefore, compress profit margins as quantity produced increases and price decreases. Over time, incumbents will grow larger and extract value mostly from the production of 'standard' products at scale. While entry will stop due to increasing barriers (it becomes harder and harder to make a profit out of the introduction of new products), larger, established firms will use technology for their primary goal – expand capacity. In this view, the product-process innovation trade-off is not linked to robots exclusively, but it is rather a feature of industry dynamics. The role played by robot technology is that of an 'accelerant', or a catalyst: robotisation can be seen as a type of process technology investment that reinforces firms' incentive to focus on capacity expansion. Especially in case of growing demand, the strategy of established companies will be that of making production scale-up cheaper (through the adoption of robots) as rapidly as possible, rather than seek for new product variants. Hence, a diseconomy of scope emerges: in mature industries (as a large share of Spanish manufacturing industries are), it becomes less and less worth to pursue both product and process innovation. Robotisation accelerates the process, as it favours scale economies. This mechanism rationalises also our baseline findings on a *persistent* negative effect. Robot adoption shapes incentives by favouring a focusing on capacity over variety expansion (hence, the negative relationship with product innovation). In turn, this action places adopters on the rails of growth and the industry on that of life-cycle pattern; as the industry evolution unfolds, the forces against product innovation gain momentum, thus persisting in the long-run. The fact that, in a few cases, the negative effects appear a few years after robot adoption takes place could be the result of inertia in absorbing sunk investments (Peters and Trunschke 2021): older product innovation investments, or current investments already planned in the past generate novelties with a delay that overlaps with new process investments. When that is the case, the trade-off between product and process strategy is hidden for some years, until it starts to 'bite'. Finally, we found evidence that the negative association between robot adoption and production innovation becomes less intense for firms that are active in robot-intensive industries. This result points at the possibility that a firm investing in robot technology within an environment that has already developed capabilities and complementary technologies to fine-tune robots could enjoy knowledge spillovers and stronger economies of learning. In this case, marginal returns in focusing exclusively on robots' fine tuning will be lower, and the firm could continue allocating a share of resources to explore product variants.

To provide descriptive support to the idea that a firm's decision on robot adoption and product innovation are shaped by diseconomies of scope as the two strategies are substitutive, we compare the dynamics of machinery investments (as a proxy for capital-driven production scale-up) against the probability and number of product innovation. Figure 4 presents the two product innovation variables (count in logs and probability, on the right y-axis) against the (log) average investment in machinery (on the left y-axis), capturing the change in investments. The time dimension is relative time to the robot adoption period (time zero). Figure 5 reports the share of peak investment in machinery against the same product innovation variables and time scale. The evidence suggests that larger changes and highest peaks in machinery investments occur, together with product innovations, in the period preceding robot adoption. The findings point at some form of anticipation effect before automation technology is deployed. A plausible interpretation is that firms develop a joint strategy on product portfolio and capacity expansion (i.e. equipment investments); robot technology is deployed to automate processes further, allowing to reap the return from previous product decisions rather than exploring new offerings (the diseconomy of scope effect we mentioned). Our descriptives and reasoning around diseconomies of scope align with the story of Miravete and Pernias (2006), according to which process and product innovation are complementary for smaller firms (that engage in demand-enhancing innovation and are more likely to adopt flexible manufacturing methods).

In summary, the possibility to adopt robots refocuses firms' attention and rebalances strategic decisions away from product innovation also in the long term, as it accelerates the movement along the industry life cycle, where firms growing larger and established companies have diseconomies of scope and economies of scale in expanding capacity. This interpretation squares well also with the findings on the specific channels driving our results. The effect we find is important in industries that are not high tech, as the forces in favour of scale are even stronger given that technology is not a key source of value as in high tech sectors. Contrariwise, firms in industries that are already robot-intensive face a less-binding trade-off, as they can internalise complementary investment and capacity-building from the external environment.

Robots adopted are not flexible enough to enable product innovation. A more in-depth take at our results is to factor-in the level of sophistication of robots. The hypothesis that robotisation as process innovation could induce product innovation is grounded on an enabling view of advanced robots, in virtue of their malleability. The underlying mechanism would be that flexible production technology counteracts the pressure exerted by diseconomies of scope, making product variety economically and technologically viable.

This will happen only if robots induce a pressure on firms' routines and decision making strong enough to make variety expansion and product diversification more attractive than they accelerate mass production; otherwise, the prevailing pressure would be to focus capacity on existing product designs, resulting in a stagnation or decrease in product innovation. An interpretation of this mechanism could be in terms of selection in the product portfolio: if robots are flexible enough, they will favour product repositioning; at the same time, they create an incentive for the exit of mature product lines that cannot be refreshed. In practice, studies found that robot technology is yet too inflexible. Perzylo and co-authors (2019) suggest that "[t]oday's industrial robots have been designed for a different scenario: large-scale, high-throughput manufacturing systems that produce one specific product (or a small set of quite similar variants) at very high quantities and with constant quality." This reinforces our claim that the robotisation-innovation nexus is shaped by industry-wide forces: small and medium-sized firms, usually very dynamic in introducing new product variants, do not have the resources and organisational capacity to adopt robots; large firms, instead, do adopt them, but they use robots as an output scale-up tool – hence, focusing production decisions towards quantity rather than variety. Instead of exerting pressure for change on a firm's decision making and organisational routines, current robots introduce rigidities (e.g. dedicated structured IT departments working on robot maintenance and upgrading).

Robots integrating more 'cognitive' capabilities, for example those powered by vision-language-action (VLA) artificial intelligence models (Brohan et al. 2023) are not yet out 'in the wild', while collaborative robots (or co-bots), one the best candidates to the role of malleable equipment, still represent a minority share of robots adopted in firms (IFR 2020). Flexibility in robots' capabilities is often related just to 'technical' flexibility. In other words, robots are increasingly malleable, but malleability is possibly being used to make a single piece of equipment executing multiple functions in already existing production processes, rather than to experiment with new ones. For instance, autonomous mobile robots (AMR) used in manufacturing and services can move along paths that are non-constrained and adjust their course by employing machine vision software and being integrated in factory IoT networks (IFR 2021). While their adoption may have effects on business models, as they change the loci of value creation and capture, their malleability is related only to physical navigation – a property that does not intersect necessarily with dimensions involved in product innovation decision.

Automation technology covered in our dataset very likely captures more traditional process improvements, in line with the quote of Perzylo et al. (2019) above. Following this argument, the negative effect we detect on product innovation might be due to the fact that we relate rather inflexible capital goods and product innovation, where the former create production economies only on those product lines that robots are designed to produce.

6. Conclusion

In this paper, we exploited firm-level data on robot adoption to study the unexplored relationship between robotisation and product innovation. As robotisation activities are a case of process innovation in which companies adopt flexible capital goods, our study is essentially assessing the nature of the interplay between recent vintages of process innovation and the introduction of new products. Given the debate around contemporary ‘smart’ technologies, one could hypothesise an enabling effect on product innovation, with entry of new varieties, designs, and in general differentiation aided by the availability of flexible production tools. However, process and product innovation investments descend from management (likely) joint strategies. We explored the possible mechanisms underpinning these simultaneous decisions to obtain a finer grained picture of the interplay between robotisation and product innovation, and the dynamic forces shaping it.

Adopting a staggered timing DiD approach supported by instrumental variable regressions, instead of an enabling effect, we find that robot adoption associates with a negative effect on product innovation, even in the long run. The main channels for this effect relate to size, age, and sector of the firm. Larger, established and less technology-intensive companies are the main drivers of the results. We rationalise and interpret the findings by building on extant theories. We suggest that the substitutive relationship between process and product innovation could be rooted either in knowledge and capabilities’ accumulation incentives, with the higher marginal returns in fine-tuning robots following adoption steering away efforts from product innovation, or in the endogenous dynamics at the core of industry life cycles. In fact, as industries (and established firms) mature, capacity expansion becomes the preferable strategy compared to variety expansion – product innovation. Robotisation can be seen as an investment shock that accelerates the dynamics and strengthen diseconomies of scope in firms’ actions. From this angle, robotisation does nothing but reinforcing industries’ incentive to engage in their ‘classic’ strategy: exploiting dynamic economies of scale by focusing on cost reduction, which, in turn, allows for capacity expansion over a small set of (standardised) products. This interpretation is accompanied by descriptive evidence on the timing of average and peak machinery investments and product innovation. Respectively, the largest change in average investment in machinery (and peak shares) and in production innovation count and probability occur in the period before robot adoption: robot technology as an automation tool is likely used to scale up and support joint strategic choices on process and products, in turn moulded by sectoral pressures. Finally, robots – even when flexible – might display enabling capabilities only when exerting broader pressures on firms’ decision-making structures. Standardised (and less high-tech) mass production processes, as well as relatively rigid organisational routines might not be able to absorb robots' full transformative potential. We take a step further by discussing whether the types of robots under analysis are the ‘right’ robots to induce innovation. In fact, not all instances of process mechanisation and robotic equipment might be malleable enough to shape technological opportunities and to affect the incentive to engage in new product discovery, design, and development.

To our knowledge, this paper is the first expanding the literature on automation to the microeconomics of innovation. While exploratory in kind, our results suggest that some dynamic mechanisms are at work within companies when robots are used to re-organise production activities. It is important to remark that we cannot easily generalise the mechanisms we hypothesised. Spain (the focus of our investigation) is a peculiar context, which experienced a surge of robotisation in the 1990s in large part due investments by the automotive industry following a reorganisation of its supply chain. Hence, a particular attention should be devoted to the country-specific patterns of industrial transformation. Still, we maintain that the non-positive relationship between robotisation and product innovation can shed some light on how the most recent phase of mechanisation of production influences other key strategies at the firm level.

It is important to stress again that most of the robotisation analysed in our empirical setting belongs to an early wave of robots used in the industrial plants. We made clear through the paper that our focus – constrained by data availability – has been on industrial robots. However, and generally speaking, the specific type of robots adopted do matter. Innovation-inducing, enabling robots are those characterised by the feature of being research tools, that is, proper ‘invention machines’, or inventions of methods of inventing (IMIs). These types of robots are used to aid the search process over, for example, the space of materials to be employed or the space of designs to be trialled and prototyped. Industrial robots such as the majority of those captured by our data might not completely lack the capability to enable new activities; however, they certainly are not IMIs, and have less scope for what concerns facilitating innovation-related search. New IMIs, such as some types of AI algorithms, are mainly software technologies, which are used in knowledge-intensive domains (and especially in services) and are not yet seamlessly integrated in the architecture and functionalities of industrial robots. By contrast, robots are employed in the manufacturing sector to increase the rate of execution and the precision of factory floor tasks under specific conditions (Combemale et al. 2021). Relatedly, another aspect of robot adoption we could not explore in this study is machine-machine substitution, with new robot vintages (likely more malleable) replacing and upgrading older (and likely less flexible) ones. This mechanism might influence the relationship between robotic automation and product innovation within the firm, turning substitutability into complementarity. While this possibility might not affect our results, that detect an average effect across the economy, it opens new interesting research questions.

Finally, our analysis has implications for policy. This focus is important and timely, given the many policy packages around the tenets of Industry 4.0 discussed and implemented in different European countries[23]. In general, our results suggest that if the policy goal is to increase rate and direction of (product) innovation, then facilitating equipment acquisition through, for instance, loans or subsidies might not serve the purpose, or even generate negative effects, if these are used to push along the trajectory of process improvement, capacity expansion, and variety ‘pruning’. Interventions of this kind might succeed only when (i) they are easing the transition to the use of those specific robots that have true enabling capabilities and (ii) they are substantial enough to revert diseconomies of scope. Diffusion policies directed at smart robots, collaborative robots and similar flexible technologies should first assess whether firms really demand or seek to deploy this kind of capital goods, in order to avoid resource misallocation. Policy makers should be wary of the degree of sophistication of the production

[23] For example, the financial support for R&D&I in the field of Industry 4.0 in Spain (https://www.mincotur.gob.es/portalayudas/industriaconectada/Paginas/Index.aspx); the Industry 4.0, now Transition 4.0 programme, in Italy (https://www.mise.gov.it/index.php/it/transizione40) (last accessed 7 December 2023).

technologies, in order to get a sense of the broad direction of the relationship between process and product strategies and, hence, to time actions appropriately. Policies of horizon scanning for new enabling technologies combined with surveys of firms' needs, as well as policies helping the formation or hiring of skills matching product innovation tasks might be more effective in a context such as the one we studied.

With this study, we highlighted a series of interesting facts and interpretations on the economic forces set in motion by the adoption of modern manufacturing capital. Hopefully, our exercise can inspire a broader research agenda for follow-up studies. For example, future research might focus more explicitly on whether current adoption involves recent waves of smart robots in order to capture additional nuances of the robotisation-innovation nexus. Another direction to follow is that of going more in-depth into the 'nano' dimension of what happens at the factory floor level where robots are implemented, using an 'insider econometrics' approach (Ichniowski and Shaw 2003). Insights from strategy research can shed light the effect of management changes that are likely to affect robot adoption and innovation. Along these lines, case studies focusing on how malleable capital is embedded into production as well as research and decision processes, such as the decision to abandon innovation projects, will help to shed further light on the relationship between robotisation and innovative activities.

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Tables

Table 1: Summary statistics by robot adopters / non-adopters (n=8,757)

	Non-adopters *[n=5,827]*	**Adopters** *[n=2,930]*	**Difference test**
Number of product innovations	1.56	3.48	***
	[11.79]	[26.86]	
New product introduction	0.15	0.28	***
	[0.35]	[0.45]	
FTE employees	93.6	315.89	***
	[202.15]	[649.76]	
R&D investment (thous.)	191.22	818.02	***
	[1253]	[4047]	
Investment in machinery (thous.)	537.5	2443.6	***
	[2917]	[8190]	
Foreign ownership (%)	9.6	22.33	***
	[27.49]	[38.99]	
Export intensity	0.14	0.24	***
	[0.23]	[0.26]	

Notes: The entries are means and standard deviations of firm level data for the estimating sample, comprising adopters (firms adopting robots in the period 1991-2016) and non-adopters (firms that never adopted robots during the period under consideration). Test scores report significance levels of i) t-tests on the equality of means for FTE employees, R&D investment, investment in industrial equipment, Foreign ownership and Export intensity; ii) Wilcoxon-Mann Whitney test for the number of product innovations given the non-normally distributed nature of the variable and iii) chi-squared test for new product introduction due to the categorical nature of the variable. * p<0.10, ** p<0.05, *** p<0.01

Table 2: Effect of robot adoption on product innovation

	# of product innovations	*New product introduction*
	(1)	(2)
5 periods before	-0.029	-0.087
	[0.071]	[0.086]
4 periods before	-0.003	-0.137+
	[0.051]	[0.078]
3 periods before	0.012	-0.019
	[0.036]	[0.057]
2 periods before	-0.061*	-0.091*
	[0.027]	[0.045]
period of adoption	-0.052**	-0.099**
	[0.020]	[0.032]
1 period later	-0.084**	-0.104*
	[0.026]	[0.049]
2 periods later	-0.144**	-0.149*
	[0.034]	[0.063]
R&D Exp	0.027**	0.032**
	[0.002]	[0.003]
Size	0.026	0.015
	[0.018]	[0.029]
Export Int	0.113	0.109
	[0.069]	[0.116]
Foreign Own	0.009	0.011
	[0.009]	[0.016]
Invest Mach	0.006**	0.003
	[0.001]	[0.003]
Firm FE	Yes	Yes
Year FE	Yes	Yes
Industry-by-year FE	Yes	Yes
Joint p-value	0.171	0.146
N (firms X year)	8757	8757
N (firms)	2456	2456

Notes. The dummy indicating one-period prior treatment status is omitted from the regression as it acts as reference period. The dependent variables are: the probability to introduce (Column 1) and the log-transformed number of new (or significantly improved) products (Column 2). Standard errors clustered at the firm level are in parentheses. + $p<0.1$, * $p<0.05$, ** $p<0.01$

Table 3: IV estimates with firm and year fixed effects

	OLS		*IV*		
	New product introduction (1)	*# product innovations* (2)	*First stage* (3)	*New product introduction* (4)	*# product innovations* (5)
Robot stock X share of exports -1			0.001**		
			[0.000]		
Robot adoption -1	-0.060*	-0.049+		-0.604**	-1.114**
	[0.016]	[0.022]		[0.097]	[0.194]
R&D Exp	0.026**	0.026**	0.003*	0.027**	0.024**
	[0.001]	[0.004]	[0.001]	[0.002]	[0.001]
Size	0.003	0.013	0.009	0.001	0.004
	[0.011]	[0.014]	[0.012]	[0.020]	[0.023]
Export Int	0.065	-0.029	-0.047+	-0.027	-0.021
	[0.091]	[0.040]	[0.029]	[0.071]	[0.055]
Foreign Own	0.005*	0.016*	-0.011*	-0.001	0.009
	[0.001]	[0.004]	[0.005]	[0.003]	[0.006]
Invest Mach	0.005**	0.005*	0.002	0.005**	0.005*
	[0.001]	[0.002]	[0.001]	[0.002]	[0.002]
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap rk Wald F statistic				74.892	74.892
N (firms)	2449	2449	1351	1351	1351
N (firms X year)	6262	6262	4260	4260	4260

Notes. This table displays OLS and IV coefficient estimates using 1998-2016 data. Regressions are based on 6,262 (4,260) firm-year observations when estimating OLS (2SLS). Columns 1-2 report results of the OLS, Column 3 first stage regression and Columns 4-5 results for 2SLS.The 2SLS uses one lag of the IV to instrument the one lagged value of robot adoption. The dependent variables are: the probability to introduce new (or significantly improved) products in columns 1 and 4 and the log-transformed number of new (or significantly improved) products in columns 2 and 5. Estimates include controls for R&D expenditure, firm size, export intensity, foreign ownership, firm and year fixed effects. Driscoll and Kraay (1998) standard errors are in parentheses. + $p<0.1$, * $p<0.05$, ** $p<0.01$

Table *4*: IV estimates with firm and year fixed effects*, excluding top 1% and top 10% of exporters*

	Excluding top 1%			*Excluding top 10%*		
	First stage	*New product introduction*	*# product innovations*	*First stage*	*New product introduction*	*# product innovations*
	(1)	(2)	(3)	(4)	(5)	(6)
Robot stock X share of exports -1	0.001**			0.001**		
	[0.000]			[0.000]		
Robot adoption -1		-0.548**	-0.931**		-0.712**	-0.465*
		[0.138]	[0.184]		[0.266]	[0.234]
R&D Exp	0.003**	0.027**	0.024**	0.002	0.028**	0.023**
	[0.001]	[0.002]	[0.001]	[0.001]	[0.002]	[0.001]
Size	0.012	0.005	0.009	-0.010	-0.019	-0.016
	[0.014]	[0.019]	[0.022]	[0.013]	[0.017]	[0.019]
Export Int	-0.025	-0.024	0.030	-0.047	-0.141	0.010
	[0.034]	[0.081]	[0.062]	[0.083]	[0.095]	[0.090]
Foreign Own	-0.009+	0.000	0.017**	0.003	0.002	0.032**
	[0.005]	[0.003]	[0.006]	[0.008]	[0.007]	[0.008]
Invest Mach	0.002	0.005**	0.004*	0.002	0.006**	0.004**
	[0.001]	[0.002]	[0.002]	[0.001]	[0.002]	[0.001]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap rk Wald F statistic		122.869	122.869		23.593	23.593
N (firms)	1334	1334	1334	1186	1186	1186
N (firms X year)	4190	4190	4190	3619	3619	3619

Notes. This table displays IV coefficient estimates using 1998-2016 data. Regressions are based on 4,190 (3,619) firm-year observations when estimating 2SLS excluding the top 1% (10%) of exporters. Columns 1-3 report results excluding the top 1% and columns 3-6 excluding the top 10%. Columns 1 and 4 show results of first stage regressions. The 2SLS uses one lag of the IV to instrument the one lagged value of robot adoption. The dependent variables are: the probability to introduce new (or significantly improved) products in columns 2 and 5 and the log-transformed number of new (or significantly improved) products in columns 3 and 6. Estimates include controls for R&D expenditure, firm size, export intensity, foreign ownership, firm and year fixed effects. Driscoll and Kraay (1998) standard errors are in parentheses. + p<0.1, * p<0.05, ** p<0.01

Table 5: Effect of robot adoption on probability of product innovation – firm size breakdown

	New product introduction		
	(1)	*(2)*	*(3)*
5 periods before	-0.024	-0.144	0.213
	[0.120]	[0.097]	[0.145]
4 periods before	-0.015	0.125	0.038
	[0.065]	[0.103]	[0.111]
3 periods before	0.070	0.078	-0.030
	[0.057]	[0.068]	[0.071]
2 periods before	-0.046	-0.074	-0.010
	[0.042]	[0.056]	[0.051]
period of adoption	-0.014	-0.057	-0.080*
	[0.034]	[0.036]	[0.040]
1 period later	-0.031	-0.054	-0.159**
	[0.044]	[0.053]	[0.056]
2 periods later	-0.067	-0.144*	-0.260**
	[0.056]	[0.063]	[0.082]
R&D Exp	0.026**	0.029**	0.025**
	[0.003]	[0.003]	[0.003]
Export Int	0.038	0.227+	0.119
	[0.103]	[0.135]	[0.134]
Foreign Own	0.058+	0.011	0.004
	[0.034]	[0.014]	[0.012]
Invest Mach	0.004**	0.008	0.018**
	[0.002]	[0.005]	[0.006]
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry-by-year FE	Yes	Yes	Yes
Joint p-value	0.307	0.046	0.519
N (firms X year)	4892	2145	1713
N (firms)	1417	600	438

Notes. Size classes refer to the average firm size over the period and are based on Eurostat (2021) definition: micro and small enterprises (less than 50 employees), medium-sized enterprises (50-249 employees) and large enterprises (250 or more employees). Regressions are based on the small firm sample in Column 1, medium-sized firms in Column 2 and large firm category in Column 3. The dummy indicating one-period prior treatment status is omitted from the regression as it acts as reference period. The dependent variables is in all columns the probability to introduce new (or significantly improved) products. Standard errors clustered at the firm level are in parentheses. + p<0.1, * p<0.05, ** p<0.01

Table 6: Effect of robot adoption on the number of product innovation – firm size breakdown

	# product innovations		
	(1)	*(2)*	*(3)*
5 periods before	-0.010	-0.156	0.085
	[0.200]	[0.133]	[0.220]
4 periods before	-0.073	-0.075	-0.078
	[0.096]	[0.157]	[0.153]
3 periods before	0.119	0.003	-0.075
	[0.095]	[0.094]	[0.123]
2 periods before	-0.022	-0.096	-0.101
	[0.060]	[0.084]	[0.096]
period of adoption	-0.075	-0.036	-0.180**
	[0.056]	[0.050]	[0.068]
1 period later	-0.073	-0.039	-0.205+
	[0.070]	[0.088]	[0.106]
2 periods later	-0.054	-0.095	-0.277+
	[0.075]	[0.115]	[0.161]
R&D Exp	0.032**	0.033**	0.032**
	[0.005]	[0.005]	[0.006]
Export Int	0.100	0.143	0.056
	[0.169]	[0.200]	[0.251]
Foreign Own	0.004	0.047*	-0.007
	[0.073]	[0.022]	[0.024]
Invest Mach	0.002	0.008	0.009
	[0.003]	[0.008]	[0.009]
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry-by-year FE	Yes	Yes	Yes
Joint p-value	0.462	0.535	0.689
N (firms X year)	4892	2145	1713
N (firms)	1417	600	438

Notes. Size classes refer to the average firm size over the period and are based on Eurostat (2021) definition: micro and small enterprises (less than 50 employees), medium-sized enterprises (50-249 employees) and large enterprises (250 or more employees).Regressions are based on the small firm sample in Column 1, medium-sized firms in Column 2 and large firm category in Column 3. The dummy indicating one-period prior treatment status is omitted from the regression as it acts as reference period. The dependent variables is in all columns the log-transformed number of new (or significantly improved) products. Similar results are obtained when firm size within each category is controlled for. Standard errors clustered at the firm level are in parentheses. + p<0.1, * p<0.05, ** p<0.01

Table 7: Effect of robot adoption on probability of product innovation – firm age breakdown

	New product introduction		
	(1)	*(2)*	*(3)*
5 periods before	-0.148	0.101	-0.012
	[0.112]	[0.128]	[0.118]
4 periods before	0.069	-0.019	-0.044
	[0.096]	[0.085]	[0.077]
3 periods before	0.022	0.078	-0.030
	[0.072]	[0.060]	[0.058]
2 periods before	-0.087+	-0.041	-0.053
	[0.051]	[0.047]	[0.045]
period of adoption	-0.040	-0.047	-0.058+
	[0.038]	[0.034]	[0.034]
1 period later	-0.034	-0.095*	-0.108*
	[0.047]	[0.047]	[0.043]
2 periods later	-0.127*	-0.168**	-0.131*
	[0.063]	[0.053]	[0.061]
R&D Exp	0.030**	0.026**	0.025**
	[0.004]	[0.003]	[0.003]
Size	0.014	0.037	0.034
	[0.034]	[0.029]	[0.037]
Export Int	0.126	0.098	0.125
	[0.136]	[0.103]	[0.127]
Foreign Own	-0.014	0.011	0.014
	[0.022]	[0.012]	[0.013]
Invest Mach	0.007**	0.005*	0.004
	[0.003]	[0.002]	[0.003]
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry-by-year FE	Yes	Yes	Yes
Joint p-value	0.166	0.212	0.824
N (firms X year)	2333	3644	2776
N (firms)	645	1047	763

Notes. Regressions are based on firms in three different age classes which approximate the three terciles of the (weighted) age distribution: less than 7 years old (Column 1), 8-26 years old (Column 2) and more than 26 years old (Column 3). The dummy indicating one-period prior treatment status is omitted from the regression as it acts as reference period. The dependent variables is in all columns the probability to introduce new (or significantly improved) products. Standard errors clustered at the firm level are in parentheses. + $p<0.1$, * $p<0.05$, ** $p<0.01$

Table 8: Effect of robot adoption on the number of product innovation – firm age breakdown

	# product innovations		
	(1)	*(2)*	*(3)*
5 periods before	-0.119	-0.141	-0.012
	[0.169]	[0.119]	[0.171]
4 periods before	0.156	-0.225*	-0.202+
	[0.188]	[0.105]	[0.103]
3 periods before	0.063	-0.017	-0.047
	[0.117]	[0.093]	[0.091]
2 periods before	-0.081	-0.052	-0.115
	[0.088]	[0.080]	[0.074]
period of adoption	-0.028	-0.132*	-0.098+
	[0.058]	[0.054]	[0.051]
1 period later	-0.029	-0.201*	-0.064
	[0.091]	[0.079]	[0.082]
2 periods later	-0.108	-0.259*	-0.076
	[0.116]	[0.102]	[0.108]
R&D Exp	0.034**	0.029**	0.033**
	[0.008]	[0.004]	[0.005]
Size	-0.075	0.056	0.023
	[0.061]	[0.040]	[0.059]
Export Int	0.350+	-0.264	0.404+
	[0.204]	[0.179]	[0.216]
Foreign Own	-0.005	0.022	0.009
	[0.027]	[0.023]	[0.028]
Invest Mach	0.005	-0.002	0.009+
	[0.004]	[0.004]	[0.005]
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry-by-year FE	Yes	Yes	Yes
Joint p-value	0.334	0.210	0.144
N (firms X year)	2333	3644	2776

Notes. Regressions are based on firms in three different age classes which approximate the three terciles of the (weighted) age distribution: less than 7 years old (Column 1), 8-26 years old (Column 2) and more than 26 years old (Column 3). The dummy indicating one-period prior treatment status is omitted from the regression as it acts as reference period. The dependent variables is in all columns the log-transformed number of new (or significantly improved) products. Standard errors clustered at the firm level are in parentheses. + p<0.1, * p<0.05, ** p<0.01

Table 9: Effect of robot adoption on product innovation – sectoral breakdown

	New product introduction			*# product innovations*		
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
5 periods before	-0.077	0.090	-0.040	-0.128	-0.009	-0.112
	[0.105]	[0.172]	[0.102]	[0.153]	[0.120]	[0.136]
4 periods before	-0.100	-0.053	0.213*	-0.219*	0.003	-0.149
	[0.070]	[0.114]	[0.086]	[0.111]	[0.148]	[0.153]
3 periods before	0.026	-0.018	0.016	-0.032	0.025	-0.069
	[0.051]	[0.072]	[0.071]	[0.092]	[0.112]	[0.096]
2 periods before	-0.087*	-0.089	0.003	-0.172**	-0.111	0.037
	[0.040]	[0.055]	[0.050]	[0.066]	[0.094]	[0.081]
period of adoption	-0.092**	-0.010	-0.037	-0.143*	-0.019	-0.109*
	[0.030]	[0.040]	[0.034]	[0.056]	[0.048]	[0.054]
1 period later	-0.119**	-0.105*	-0.022	-0.141+	-0.090	-0.065
	[0.039]	[0.052]	[0.051]	[0.081]	[0.089]	[0.084]
2 periods later	-0.119*	-0.187**	-0.146*	-0.221*	-0.169+	-0.010
	[0.052]	[0.058]	[0.070]	[0.101]	[0.101]	[0.127]
R&D Exp	0.026**	0.026**	0.028**	0.037**	0.024**	0.030**
	[0.003]	[0.003]	[0.003]	[0.005]	[0.005]	[0.006]
Size	-0.002	0.042	0.056	-0.049	0.091+	0.052
	[0.026]	[0.033]	[0.039]	[0.045]	[0.047]	[0.058]
Export Int	0.142	0.215+	-0.010	0.320	0.159	-0.226
	[0.104]	[0.128]	[0.127]	[0.219]	[0.162]	[0.177]
Foreign Own	0.011	0.024	-0.005	0.022	0.014	-0.014
	[0.013]	[0.018]	[0.015]	[0.029]	[0.026]	[0.029]
Invest Mach	0.005**	0.006*	0.008*	0.004	0.003	-0.002
	[0.002]	[0.003]	[0.004]	[0.003]	[0.003]	[0.007]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Joint p-value	0.080	0.537	0.091	0.033	0.578	0.654
N (firms X year)	4500	2111	2146	4500	2111	2146
N (firms)	1282	584	590	1282	584	590

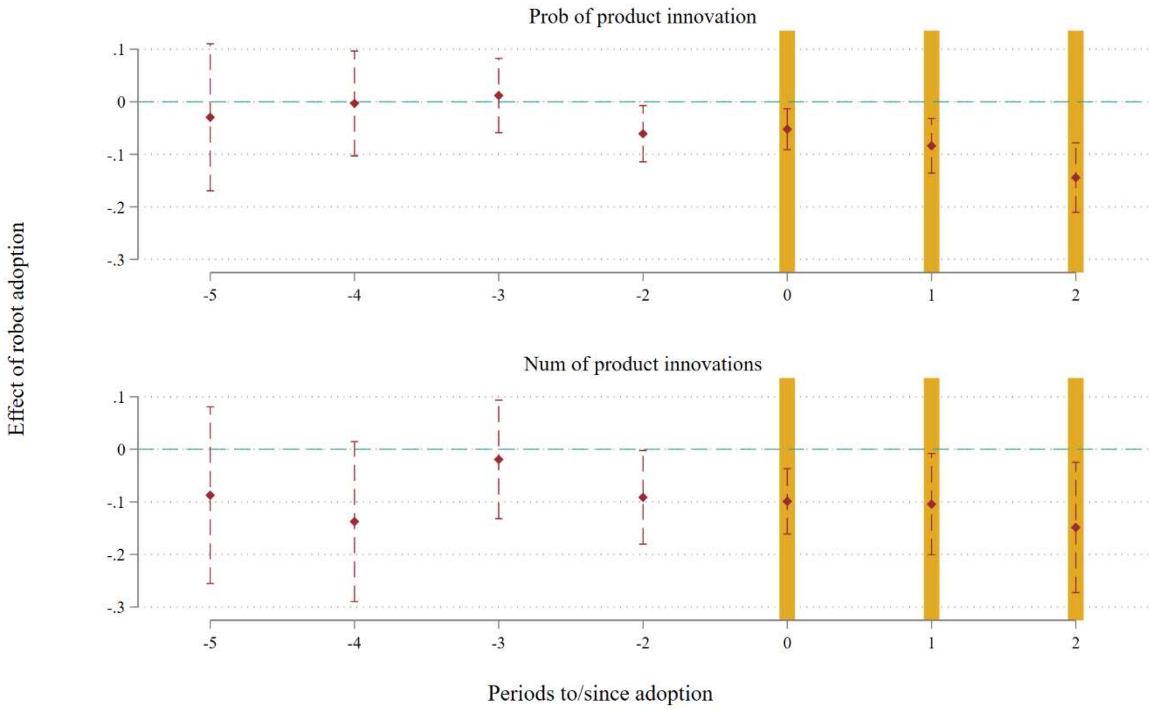
Notes. Results are reported for firms in low-tech industries (Columns 1 and 4), for firms in medium-tech industries (Columns 2 and 5) and for firms in high-tech industries (Columns 3 and 6). Industry classification follows OECD (2016) and aggregates medium-high tech and medium-low tech due to the low number of cases. The dummy indicating one-period prior treatment status is omitted from the regression as it acts as reference period. The dependent variables are: the probability to introduce new (or significantly improved) products in Columns 1-3 and the log-transformed number of new (or significantly improved) products in Columns 4-6. Standard errors clustered at the firm level are in parentheses. + p<0.1, * p<0.05, ** p<0.01

Table 10: Effect of robot adoption on product innovation – robot intensive vs non robot intensive industries

	New product introduction		*# product innovations*	
	(1)	*(2)*	*(3)*	*(4)*
3 periods before	0.036	0.126+	-0.151	0.103
	[0.083]	[0.076]	[0.106]	[0.090]
2 periods before	-0.057	-0.072	-0.097	0.004
	[0.064]	[0.053]	[0.094]	[0.090]
period of adoption	-0.050	-0.085*	-0.059	-0.123*
	[0.038]	[0.033]	[0.049]	[0.052]
1 period later	-0.063	-0.142**	-0.033	-0.206**
	[0.049]	[0.048]	[0.072]	[0.074]
2 periods later	-0.158*	-0.161*	-0.084	-0.222*
	[0.061]	[0.063]	[0.098]	[0.109]
R&D Exp	0.022**	0.027**	0.016**	0.030**
	[0.004]	[0.003]	[0.004]	[0.004]
Size	0.065+	0.014	0.007	-0.021
	[0.035]	[0.035]	[0.051]	[0.046]
Export Int	0.049	-0.060	0.088	0.068
	[0.123]	[0.129]	[0.162]	[0.171]
Foreign Own	0.013	-0.002	0.021	0.018
	[0.019]	[0.017]	[0.029]	[0.021]
Invest Mach	0.005+	0.006*	0.004	0.005
	[0.003]	[0.002]	[0.004]	[0.004]
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry-by-year FE	Yes	Yes	Yes	Yes
Joint p-value	0.443	0.017	0.326	0.445
N (firms X year)	2299	3213	2299	3213
N (firms)	779	1061	779	1061

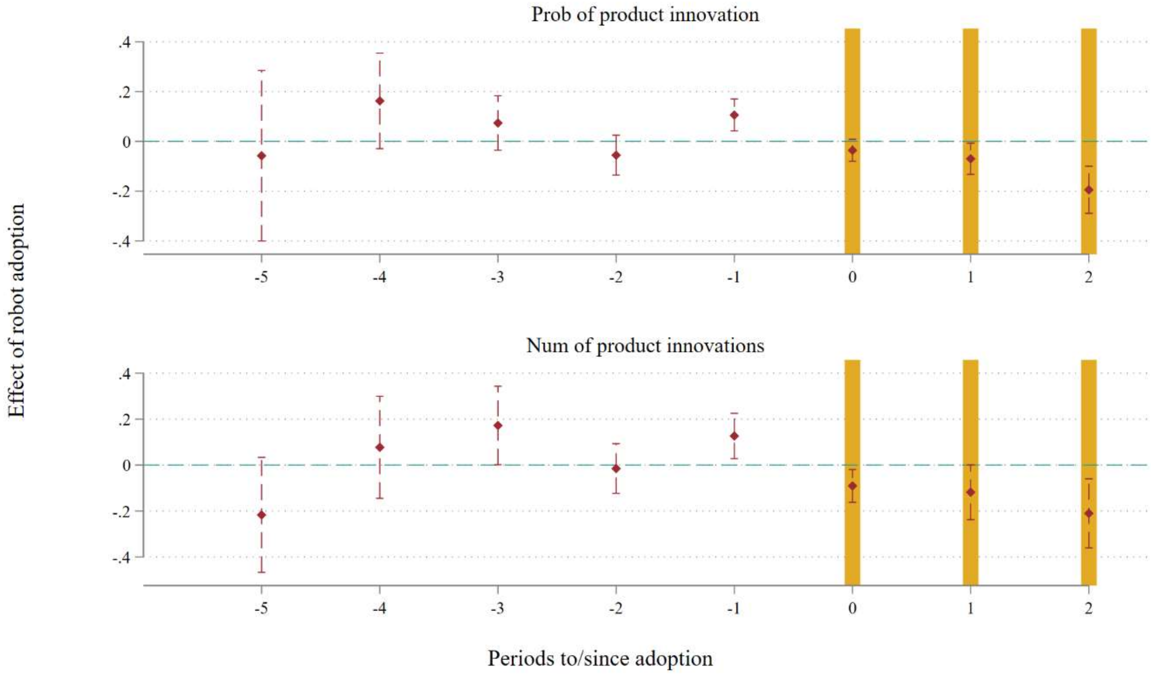
Notes. Regressions are based on 2,299 or 3,213 firm-year observations depending on the sample employed. Pre-treatments are consolidated to t-3 for older periods due to the low number of firms. The dummy indicating one-period prior treatment status is omitted from the regression as it acts as reference period. The dependent variable in Columns 1 and2 is the probability to introduce new (or significantly improved) products. The dependent variable in Columns 3 and 4 is the log-transformed number of new (or significantly improved) products. Columns 1 and 3 report results for firms in robot intensive industries (industries with an operational stock of industrial robots below the world median), while Columns 2 and 4 report results for firms in non-robot intensive industries (industries with an operational stock of industrial robots greater or equal the world median). Standard errors clustered at the firm level are in parentheses. + p<0.1, * p<0.05, ** p<0.01

Figure 1. Estimated effect of robot adoption on product innovation



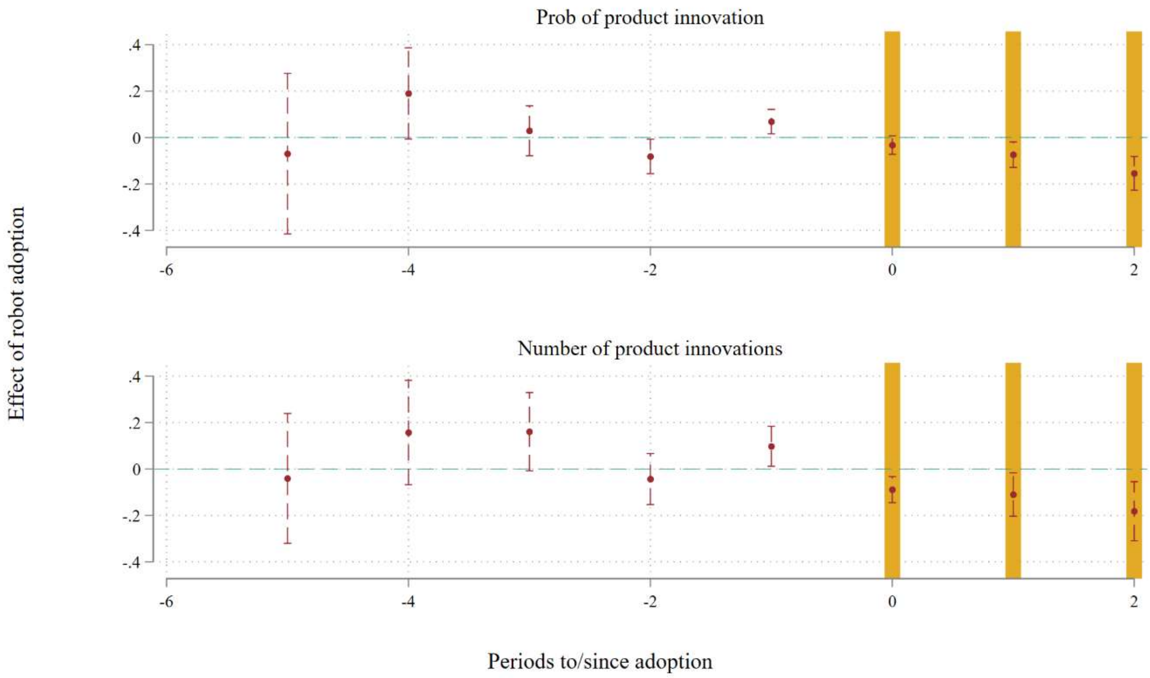
Notes. The figure shows the estimated effects of robot adoption on the two dependent variables: the probability to introduce new (or significantly improved) products (upper figure) and the log-transformed number of new (or significantly improved) products (lower figure). The figure reports the coefficients and standard errors from Table 2 for the dummies of robot adoption: 5 periods before, 4 periods before, 3 periods before 2 periods before, period of adoption, 1 period later and 2 periods later. The dummy indicating one-period prior treatment status is omitted as it acts as reference period. Controls include for the relevant period: firm size (the average number of full-time equivalent employees), the deflated total expenditure in R&D, the deflated investment in industrial machinery, the share of foreign ownership (both as direct and indirect foreign capital participation), the share of the total value of exports over sales, firm, year and industry-by-year fixed effects. Confidence intervals at the 95% level.

Figure 2: Estimated effect of robot adoption on product innovation - Callaway and Sant'Anna (2021) estimator



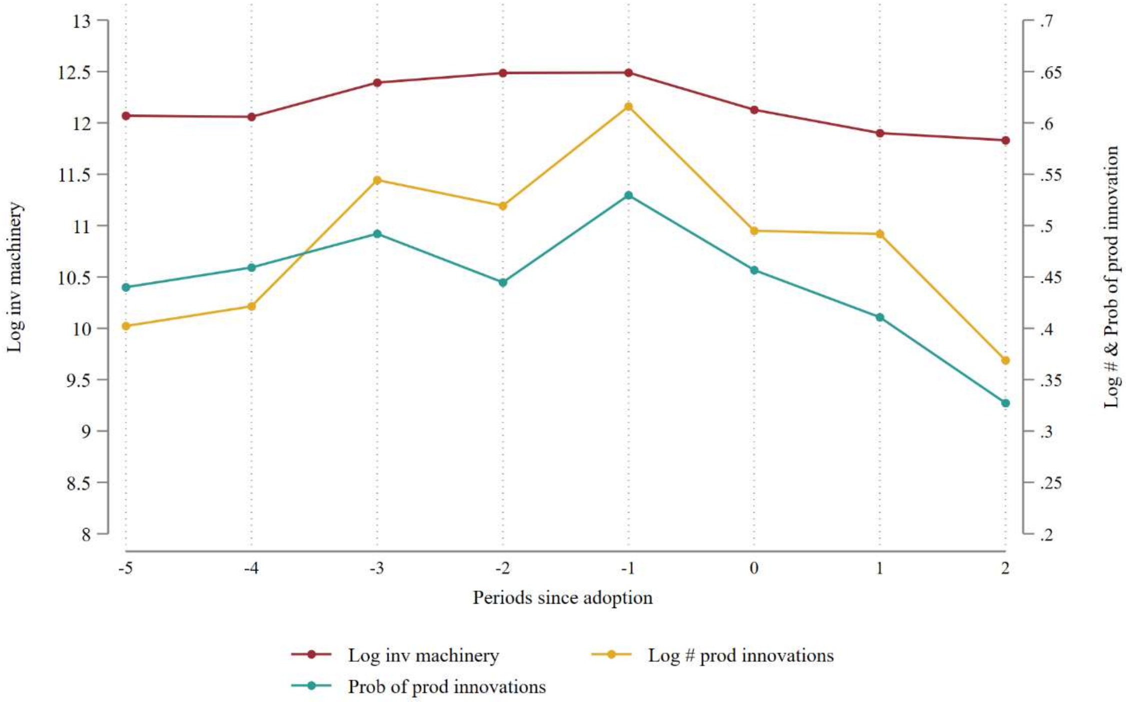
Notes. The figure shows the estimated effects of robot adoption on the two dependent variables: the probability to introduce new (or significantly improved) products (upper figure) and the log-transformed number of new (or significantly improved) products (lower figure). The figure reports the coefficients and standard errors from the estimator of Callaway and Sant'Anna (2021) for the dynamic treatment effects: 5 periods before, 4 periods before, 3 periods before, 2 periods before, 1 period before, period of adoption, 1 period later and 2 periods later. Controls include for the relevant period: firm size (the average number of full-time equivalent employees), the deflated total expenditure in R&D, the deflated investment in industrial machinery, the share of foreign ownership (both as direct and indirect foreign capital participation), the share of the total value of exports over sales, firm, year and industry-by-year fixed effects. Confidence intervals at the 95% level.

Figure 3: Event study with heterogeneous treatment effects robust to switchers - De Chaisemartin, and d'Haultfoeuille (2022).



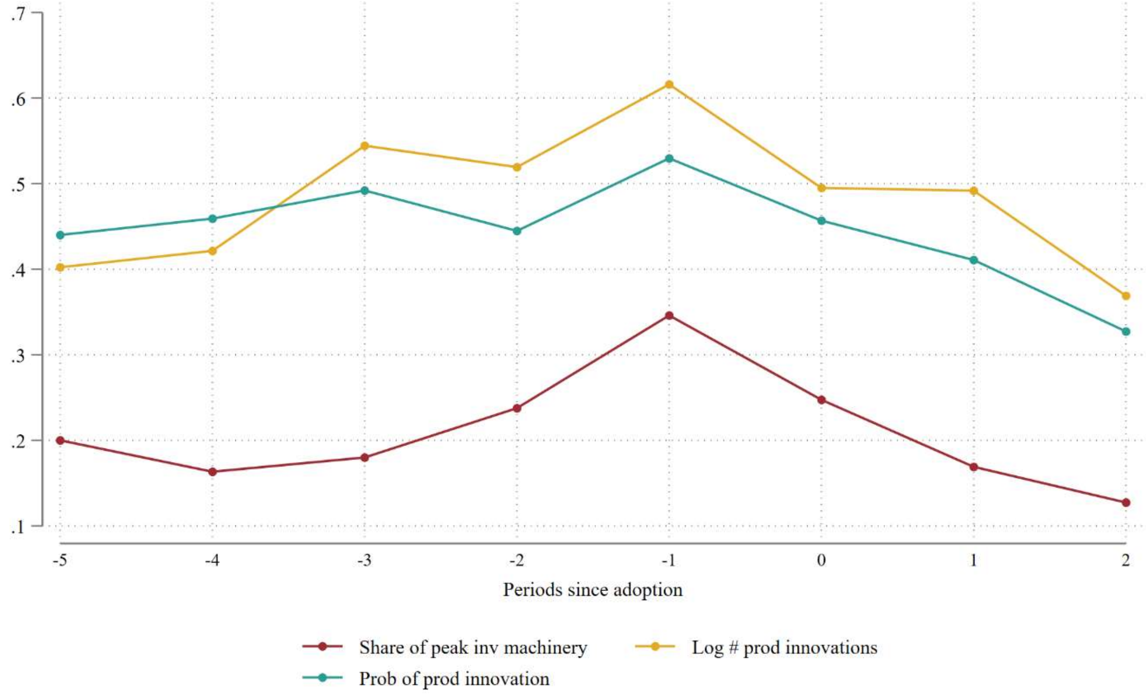
Notes. The figure shows the estimated effects of robot adoption on the two dependent variables: the probability to introduce new (or significantly improved) products (upper figure) and the log-transformed number of new (or significantly improved) products (lower figure). The figure reports the coefficients and standard errors from the estimator of De Chaisemartin,and d'Haultfoeuille (2022) for the dynamic treatment effects: 5 periods before, 4 periods before, 3 periods before, 2 periods before, 1 period before, period of adoption, 1 period later and 2 periods later. Controls include for the relevant period: firm size (the average number of full-time equivalent employees), the deflated total expenditure in R&D, the deflated investment in industrial machinery, the share of foreign ownership (both as direct and indirect foreign capital participation), the share of the total value of exports over sales, firm, year and industry-by-year fixed effects. Confidence intervals at the 95% level.

Figure 4: Average investment in machinery (logarithm) and product innovation indicators



Notes. This figure plots the log of the average investment in machinery (left y axis) and the log of the number and the probability of product innovation (right y axis) relative to the firms' period of adoption (from 5 years before to 2 years after adoption).

Figure *5*: Peak investments in machinery (share of firms) and product innovation indicators



Notes. This figure plots the share of firms with peak investments in machinery (left y axis) and the log of the number and the probability of product innovation (right y axis) relative to the firms' period of adoption (from 5 years before to 2 years after adoption). Peak investments are defined as the maximum value of investment in machinery by the firm over the overall observation period.

Appendix

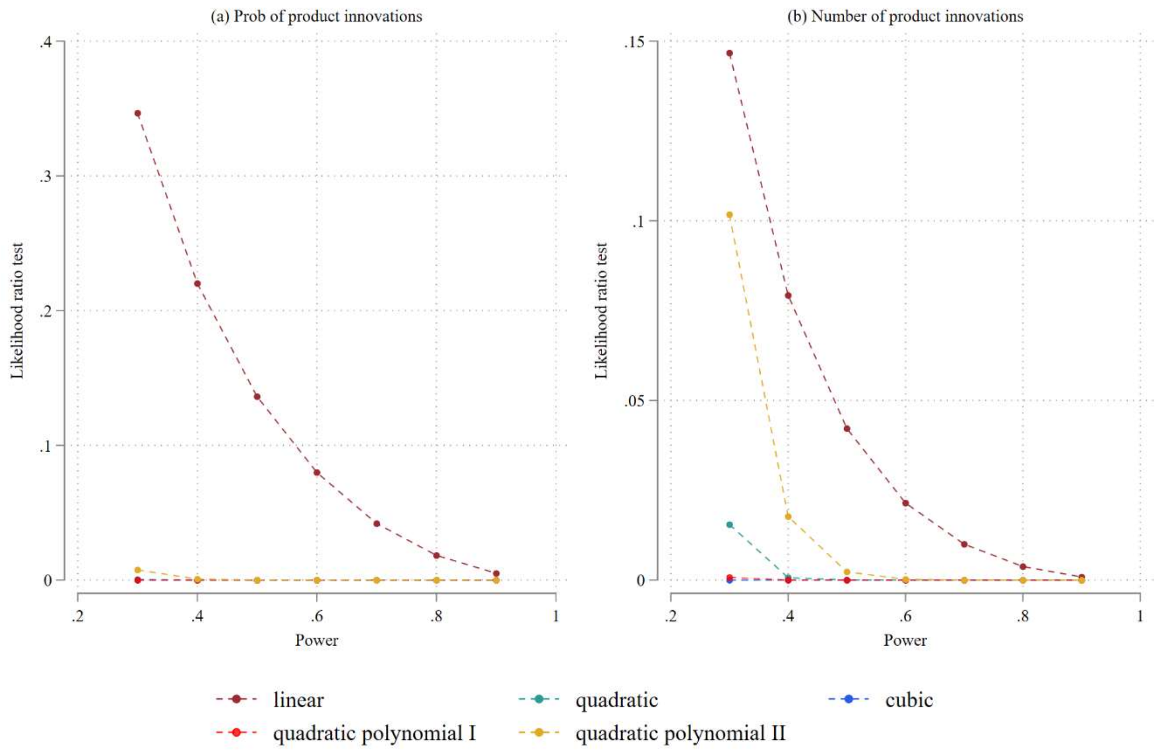
Table *A 1* Summary of pre-period coefficients significance

Table number	*Table description*	*Column number*	*Column description*	*Dependent variable*	*# significant pre-periods at the 5% level*	*Joint p-value*	*Likelihood ratio from Roth (2022)*
2	Baseline	1	Prob of product innovation	Prob of product innovation	1	0.171	0.009
2	Baseline	2	# of product innovations	# of product innovations	1	0.146	0.001
3	Firm size breakdown	1	small firms	Prob of product innovation	0	0.307	0.02
3	Firm size breakdown	2	medium-sized firms	Prob of product innovation	0	0.046	0.04
3	Firm size breakdown	3	large firms	Prob of product innovation	0	0.519	0.0004
4	Firm size breakdown	1	small firms	# of product innovations	0	0.462	0.04
4	Firm size breakdown	2	medium-sized firms	# of product innovations	0	0.535	0.08
4	Firm size breakdown	3	large firms	# of product innovations	0	0.689	0.003
5	Firm age breakdown	1	young firms	Prob of product innovation	1	0.166	0.02
5	Firm age breakdown	2	medium-aged firms	Prob of product innovation	0	0.212	0.0005
5	Firm age breakdown	3	old firms	Prob of product innovation	0	0.824	0.03
6	Firm age breakdown	1	young firms	# of product innovations	0	0.334	0.001
6	Firm age breakdown	2	medium-aged firms	# of product innovations	1	0.21	0.45
6	Firm age breakdown	3	old firms	# of product innovations	0	0.144	0.17

7	Sectoral breakdown	1	low-tech firms	Prob of product innovation	1	0.08	0.16
7	Sectoral breakdown	2	medium-tech firms	Prob of product innovation	0	0.537	0.008
7	Sectoral breakdown	3	high-tech firms	Prob of product innovation	1	0.091	0.0003
7	Sectoral breakdown	4	low-tech firms	# of product innovations	2	0.033	0.25
7	Sectoral breakdown	5	medium-tech firms	# of product innovations	0	0.578	0.0003
7	Sectoral breakdown	6	high-tech firms	# of product innovations	0	0.654	0.1
8	Breakdown by industrial robot intensiveness	1	robot intensive industries	Prob of product innovation	0	0.443	0.02
8	Breakdown by industrial robot intensiveness	2	non robot intensive industries	Prob of product innovation	1	0.017	0.005
8	Breakdown by industrial robot intensiveness	3	robot intensive industries	# of product innovations	0	0.326	1.87
8	Breakdown by industrial robot intensiveness	4	non robot intensive industries	# of product innovations	1	0.445	0.001

Notes: The table shows the number of pre-period coefficients that are significant at the 95 percent level, the p-value for a chi-squared test of joint significance, and the value of the likelihood ratio as proposed by Roth (2022) at the 90% power level (the probability one would find a significant pre-trend under the hypothesised pre-trend). The likelihood ratio test in Roth shows the likelihood of observing the coefficients from our estimates conditional on having an inverted U-shaped hypothesised pre-trend over the likelihood of observing them under parallel trends. This indicate how much less likely are the observed coefficients under the hypothesised pre-trend compared to under parallel trend. A ratio below 1 signals a lower probability of obtaining the coefficients under the chosen pre-trend compared to a parallel trend.

Figure *A 1*: sensitivity analysis of Roth test for baseline models



Notes. The figure shows sensitivity analysis for different functional forms and different power levels of the Roth test for the baseline regression model (Table 2). Figure a (b) plots, for the model estimating the probability (number) of product innovations, the value of the Roth likelihood test (i.e. likelihood of observed coefficients under the hypothesised trend over the likelihood of observed coefficients under parallel trend) against different power levels (i.e. the probability one would find a significant pre-trend under the hypothesised pre-trend) for different hypothesised trends(linear, quadratic, cubic, quadratic polynomial I and quadratic polynomial II).