



Artificial intelligence as a complement to other innovation activities and as a method of invention

Guillermo Arenas Díaz , Mariacristina Piva & Marco Vivarelli

To cite this article: Guillermo Arenas Díaz , Mariacristina Piva & Marco Vivarelli (09 Jun 2026): Artificial intelligence as a complement to other innovation activities and as a method of invention, *Economics of Innovation and New Technology*, DOI: [10.1080/10438599.2026.2682250](https://doi.org/10.1080/10438599.2026.2682250)

To link to this article: <https://doi.org/10.1080/10438599.2026.2682250>



© 2026 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group



Published online: 09 Jun 2026.



Submit your article to this journal [↗](#)



Article views: 199



View related articles [↗](#)



View Crossmark data [↗](#)

Artificial intelligence as a complement to other innovation activities and as a method of invention

Guillermo Arenas Díaz^a, Mariacristina Piva^b and Marco Vivarelli^{a,c,d}

^aDepartment of Economic Policy, Università Cattolica del Sacro Cuore, Milano, Italy; ^bDepartment of Economic Policy, Università Cattolica del Sacro Cuore, Piacenza, Italy; ^cUNU-MERIT, Maastricht, The Netherlands; ^dIZA, Bonn, Germany

ABSTRACT

This study investigates the relationship between Artificial Intelligence (AI) and innovation inputs in Spanish manufacturing firms. While AI is increasingly recognized as a driver of productivity and economic growth, its role in shaping firms' innovation strategies remains underexplored. Using firm-level data, our analysis focuses on whether AI complements innovation inputs – specifically R&D and Embodied Technological Change (ETC) – and whether AI can be considered as a Method of Invention, able to trigger subsequent innovation investments. Results show a positive association between AI adoption and both internal R&D and ETC, in a static and a dynamic framework. Furthermore, empirical evidence also highlights heterogeneity, with important peculiarities affecting large vs small firms and high-tech vs low-tech companies. These findings suggest that AI may act as both a complement and a catalyst, depending on firm characteristics.

ARTICLE HISTORY

Received 3 October 2025
Accepted 26 May 2026

KEYWORDS

Artificial intelligence;
method of invention; R&D;
innovation inputs; innovative
complementarities



JEL CODES

O31; O32

1. Introduction

Artificial Intelligence (AI) is a transformative technology that is reshaping how firms produce and introduce new products to the market. Damioli, Van Roy, and Vertesy (2021, 2025) argue that AI is emerging as a key driver of economic growth and productivity. Another recent and important stream of literature tries to assess the twofold nature of AI technologies in terms of complementarity/substitution of the workforce (see Acemoglu et al. 2022; Brunetti, Dughera, and Ricci 2025; Damioli et al. 2024; Felten, Raj, and Seamans 2021; Greenan, Guarascio, and Reljic 2025; Montobbio et al. 2024).

However, there is a notable scarcity of empirical research assessing the impact of AI on firms' innovation performance, particularly regarding its role as a complement to other innovation inputs and as a method of invention. While some scholars have examined

CONTACT Mariacristina Piva  mariacristina.piva@unicatt.it  Department of Economic Policy, Università Cattolica del Sacro Cuore, Piacenza, 29122, Italy

© 2026 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group

This is an Open Access article distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/4.0/>), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited. The terms on which this article has been published allow the posting of the Accepted Manuscript in a repository by the author(s) or with their consent.

the role of AI in capability development (e.g. Sjödin et al. 2021), it remains unclear how AI-driven capabilities interact with other types of firm capabilities, such as R&D investments (Mariani, Machado, and Nambisan 2023).

This study seeks to bridge this gap by addressing two key research questions. First, is AI a complement (following in spirit Milgrom and Roberts 1990, 1995) to R&D and other innovation inputs, such as Embodied Technology Change (ETC, defined as the adoption and implementation of innovative machineries and equipment, new software etc, see Freeman, Clark, and Soete 1982; Salter 1960; Solow 1960)? Second, can AI be considered a method of invention, namely fostering an increase in the subsequent investment in other innovation inputs? The first research question will be investigated through a contemporaneous correlation analysis, while the second issue will be tested through an econometric specification with a dynamic structure.

The dataset used to address our research questions comes from the 'Encuesta sobre Estrategias Empresariales' (ESEE), a survey of Spanish manufacturing firms covering the period from 1990 to 2022.¹ However, queries specifically related to AI are only available for the years 2018 and 2022, when AI started becoming relevant at the firm-level.²

This information first allows us to test the unconditional and conditional complementarity between AI and other innovation inputs. We follow the methodology proposed by Mohnen and Röller (2005) and Catozzella and Vivarelli (2014), which involves a descriptive analysis of both unconditional and conditional correlations. Then, we assess the impact of AI adoption in 2018 on innovation inputs in 2022, including internal and external R&D expenditure and ETC. All specifications control for firm size and other firm characteristics and include regional and industry fixed effects.

The results from the complementary analysis indicate a certain degree of complementarity between AI and both internal R&D and ETC. These correlations are positive and statistically significant in both the unconditional and conditional analyses. Furthermore, in the econometric analysis, we find a positive impact of AI adoption (in 2018) onto subsequent investments in total R&D, internal R&D and ETC (in 2022), suggesting that AI plays the role of a method of invention, enhancing a firm's innovation capacity in terms of its standard innovation inputs. However, heterogeneity across innovative firms emerges, with these effects mainly driven by large firms and companies operating in the high-tech industries.

The remainder of the paper is structured as follows. Section 2 sets the context and reviews the relevant literature. Section 3 describes the data and the adopted methodology. Section 4 discusses the empirical results and Section 5 concludes.

2. The context and the extant literature

Artificial Intelligence represents a new paradigm that is transforming economic structures and society as a whole, fostering the emergence of intelligent societies (Damioli et al. 2025; Lábaj, Oleš, and Procházka 2025; Miller 2019). Liu et al. (2020) and Yogesh et al. (2021) report that AI is increasingly being applied in the manufacturing, finance, education, healthcare, and logistics sectors. According to Cockburn, Henderson, and Stern (2019), Holm et al. (2023), Batabyal, Kourtit, and Nijkamp (2025) and Calvino, Reijerink, and Samek (2025), AI has the potential to become a powerful driver of innovation, productivity gains, and economic growth.³

But what exactly is Artificial Intelligence? According to Aghion, Jones, and Jones (2017), AI refers to ‘the capability of a machine to imitate intelligent human behaviour’ or ‘an agent’s ability to achieve goals in a wide range of environments’. Similarly, Liu et al. (2020) highlight a common element across AI definitions: the performance of human-like intelligent activities programmed to accomplish specific tasks. More precisely, AI systems can mimic human thinking and perform roles and tasks that were previously carried out by people.⁴

In mimic humans, Agrawal, Gans, and Goldfarb (2019) conceptualize AI principally as a tool that dramatically reduces the cost of prediction. This shift has deep implications for firms, as prediction is a fundamental input in decision-making processes, including decisions affecting R&D investment and innovation strategies. In this new framework, AI does not replace judgment; rather, it separates prediction from decision-making, allowing humans to increasingly focus on interpreting and acting on AI-generated forecasts.⁵ Moreover, Agrawal, Gans, and Goldfarb (2024), discussing the impact of AI adoption on organizations, consider how interactions between multiple tasks influence its effectiveness. The study, modelling both modular and non-modular systems, finds that AI adoption increases decision variation, posing challenges in organizations with interdependent decisions (as those related to innovation activities).

Indeed, the theoretical foundation of this approach is rooted in the concept of complementarities, as developed by Milgrom and Roberts back in the ‘90s (1990, 1995). Firm decisions are often interdependent, such that the marginal return to one activity increases with the level of another. This framework implies that firms do not choose technologies, organizational practices, or innovation investments as separate steps, but rather as part of coherent systems of mutually reinforcing elements. Within this perspective, complementarities arise when the joint adoption of two practices yields higher results than the sum of the separate effects. This insight has important implications as it suggests that partial adoption of complementary practices may yield limited benefits, while joint adoption can generate considerable performance improvements. Building on this framework, a large empirical literature has documented complementarities between technological and organizational innovations. For instance, Bocquet, Brossard, and Sabatier (2007), in a sample of French companies, show complementarity effects between strategies, organization and information technologies. Stucki and Wochner (2019), in the Swiss case, provide evidence that technology effectiveness depends on specific complementary organizational changes. More recently and with a focus on the Spanish case (PITEC data), Vahter and Vadi (2024) explore the dynamic nature of complementarities between technological and organizational innovations of firms investigating how the formation and ending of the joint adoption of these two core types of innovation are associated with firm performance.

Although the literature discussed above mainly focuses on the complementarity between technological and organizational change, it opens the way to conceptualize the relationship between AI and R&D as a case of strategic complementarity. In fact, AI adoption enhances firms’ capabilities in data processing, prediction, and the automation of codifiable tasks, thereby increasing the marginal productivity of R&D activities such as idea screening, experimentation, and problem-solving. At the same time, in-house R&D might expand the range of problems and application domains in which predictive tools and data-driven methods can be deployed, increasing the benefits from AI

investment. This bidirectional reinforcement is close to the notion of supermodularity developed by Milgrom and Roberts (1990, 1995)⁶ and suggests that the possible association between AI and R&D (and other innovation inputs) may reflect joint optimization rather than independent choices.

Indeed, AI encompasses a wide range of technologies, including machine learning, deep learning, natural language processing, computer vision, speech recognition, intelligent decision support systems, intelligent robotic systems, as well as the novel application of these tools across various domains (OECD 2024). As an initial approach, Cockburn, Henderson, and Stern (2019) classified AI into two categories: automation-oriented applications, such as robotics, and emerging developments, including natural language processing (NLP) and deep learning. This distinction is important because AI (particularly with regard to the latter categories) can be considered a ‘General Purpose Technology (GPT)’, and even a ‘method of invention’.

An innovation is considered a General Purpose Technology (GPT) when it satisfies three key characteristics: (1) pervasiveness, (2) innovational complementarities that give rise to increasing returns to scale in innovation and (3) an inherent potential for continuous technological improvement. The first characteristic refers to the innovation’s pervasive applicability across multiple sectors. As a GPT evolves and advances, it diffuses throughout the economy, fostering broad-based productivity gains (Bresnahan and Trajtenberg 1995). Obviously enough, this feature fully applies to the case of AI. The second characteristic refers to innovational complementarities (IC), whereby the productivity of R&D and other innovation activities directly benefits from the innovation in the GPT itself (Bresnahan and Trajtenberg 1995). These complementarities propagate throughout the economy, amplifying the broader impact of technological advancement onto productivity and economic growth. Finally, the third feature of a GPT stems from its role as an enabling technology, one that opens new innovative opportunities rather than providing a final solution. In the particular case of AI, its enabling role is rooted in the fact that AI tools (particularly deep learning and NLP) can be used as research devices that open new avenues of inquiry and enhance innovation productivity (Cockburn, Henderson, and Stern 2019).

The three GPT characteristics (which are so pronounced in the inner nature of AI) open the way to consider AI as a method of invention (Mol). This idea was originally proposed by Griliches (1957) in his seminal study of hybrid corn, where the discovery of double cross hybridization was considered as a Mol. Rather than producing a single new corn variety, the innovation enabled a method that could be applied to generate many new varieties, significantly enhancing agricultural productivity. In other words, an innovation qualifies as a Mol when it constitutes a new way of generating innovations with broad applicability.

Indeed, AI – particularly through deep learning, neural networks and NLP – appears to hold strong potential as a research tool for solving those classification and prediction problems that characterize the innovation activities, so reducing costs and improving performance in R&D projects. Much like hybrid corn, AI expands the ‘innovation playbook’ by enabling the discovery of new ideas and the solution of trade-offs, thereby altering the way scientific research is conducted (Cockburn, Henderson, and Stern 2019). Therefore, AI can be seen as a universal technology that can support other innovations.⁷ However, the AI revolution requires allowing complementary inventions to develop, businesses to be reorganized, and workers to upskill in order to diffuse across the economy (Brynjolfsson, Rock, and Syverson 2019; Damioli, Van Roy, and Vertesy 2021).

More in general, when considering the AI role in science, Bianchini, Müller, and Pelletier (2022) discuss how AI is transforming scientific discovery. Rather than merely accelerating existing research, AI is becoming a tool for generating new hypotheses, designing experiments, and interpreting complex data. By automating and enhancing cognitive tasks, AI enables scientists to uncover patterns and insights that were previously difficult to reach or even to imagine. Therefore, AI has the potential to increase research efficiency and foster interdisciplinarity.

We now turn our attention to those studies that have empirically examined the relationship between AI and innovation performance. We have identified three main groups of contributions: (1) studies that use patents as a proxy for AI; (2) studies that use specific technologies (particularly robots and big data) as a proxy for AI; and (3) studies that rely on survey data, such as the Community Innovation Survey (CIS).

Patents are a widely used instrument for measuring various aspects of innovation. With regard to AI, Cockburn, Henderson, and Stern (2019), drawing on data from the USPTO and published articles, examine the changing nature of measurable innovation outputs in AI. The results suggest a shift since 2009 toward the growing importance of application-oriented machine learning research. Similarly, Fujii and Managi (2018), using data from WIPO's PATENTSCOPE from 2000 to 2016, show a transition from biological and knowledge-based models to more specific mathematical models and other AI technologies, particularly in the United States and Japan. More recently, Damioli et al. (2025) – using data from the European Patent Office (EPO) covering the period 2000–2016 – investigate whether AI is initiating a new technological paradigm, using the perspective of evolutionary neo-Schumpeterian economics. Among their findings, one stands out: AI technologies contribute to the generation and acceleration of further innovations.

Another way to assess the impact of AI is using Big Data as a proxy: while Big Data cannot, in a strict sense, be considered AI, it is often regarded as a key component of it. Most studies examining the relationship between Big Data and innovation performance report a positive association, for example, with innovative competitive advantage and with agile product and service co-creation processes (e.g. Ghasemaghahi and Calic 2019; Lozada, Arias-Pérez, and Perdomo-Charry 2019).⁸ One interesting study that uses Big Data as a proxy for AI is put forward by Niebel, Rasel, and Viète (2019). The authors use multiple waves of the German ZEW ICT survey (2000, 2002, 2004, 2007, 2010, and 2015) and find that Big Data is a significant determinant of both the likelihood that a firm becomes a product innovator and of the market success of its product innovations.

Turning our attention to those studies using survey data, Rammer, Fernández, and Czarnitzki (2022) explicitly adopt a definition of AI in their analysis. Using data from the German component of the 2018 Community Innovation Survey (CIS), which follows the Oslo Manual guidelines, the authors estimate the relationship between AI and innovation outcomes using OLS and Probit models. Their findings reveal a positive association between AI adoption and product innovation (both in binary terms and in terms of sales attributable to new products). In particular, the results indicate that AI use is positively associated with annual sales from radical product innovations. With a slightly different approach, Babina et al. (2024) propose a new measure of firms' investments in AI based on their intensity of AI-skilled hiring. In their study, AI adoption shows an enabling effect shortening experimentation time and increasing product variety thanks to better predictions of demand (while not affecting process innovation).

Based on the literature discussed in this section, we identify a gap in the existing research: while the extant literature provides evidence of a positive relationship between AI adoption and innovation performance (for instance, measured in terms of product innovation), the relationship between AI and innovation inputs has never been investigated. Indeed, if AI is a GPT and a Mol, we should expect complementarity and boosting effects on innovation inputs as well. In other words, AI adoption should come hand in hand with an increase in expenditures in R&D and other innovation inputs.

In more detail, AI might foster R&D investments since it makes faster and more precise (and so more profitable) the search, experimentation, and problem-solving tasks associated with R&D activities; in so doing, AI may raise the marginal productivity of R&D activities in a way that matches closely the notion of AI as a method of invention (see Bianchini, Müller, and Pelletier 2022). By the same token, AI might enforce and make more profitable the adoption and implementation of innovative machineries, innovative intermediate inputs, new software and other forms of embodied technological change (ETC).

These considerations open the way to the two following research questions: (1) Is AI a complement to R&D, and/or to other innovation inputs, such as ETC? (see Section 4.1); (2) Can AI adoption be considered a Mol, thereby fostering subsequent investments in R&D and other innovation inputs? (see Section 4.2). Indeed, if AI is a Mol, R&D projects and other innovation inputs become more effective in generating innovative outputs, and thus their expected profitability increases; therefore, the incentive to invest in these activities should significantly increase.

3. Data and methodology

To deal with the previous research questions, we use the Survey on Business Strategies (ESEE) conducted by the Ministry of Industry and the SEPI Foundation in Spain. The ESEE survey is representative and provides longitudinal data on firms in Spain's manufacturing sector since 1990. On average, 1,800 companies have been surveyed from 1990 to 2023 through a questionnaire with 107 questions that contain information on the company's balance sheet, firm characteristics, markets, technological developments, foreign trade, employment, and so on. The ESEE has been widely used in previous studies. For instance, to analyse the barriers to innovation (González, Jaumandreu, and Pazó 2005), to assess the persistence of innovation (Triguero, Córcoles, and Cuerva 2014), to examine the relationship between R&D drivers and firm's age (García-Quevedo, Pellegrino, and Vivarelli 2014).⁹

3.1. Identification strategy and descriptive statistics

ESEE has included a question related to the use of Technologies 4.0 every four years¹⁰ since 2018. We use this question to identify AI users and to examine the contemporaneous complementarity between AI and innovation inputs¹¹ in 2022, as well as the impact of AI adoption in 2018 onto innovation inputs in 2022 (AI as a Mol).¹² The AI indicator in our analysis includes the following four technologies: (1) automatically guided vehicles (e.g. autonomous vehicles, drones); (2) machine learning / data-driven management / big data; (3) computer vision/machine vision; and (4) natural language processing. Each of these AI technologies is assessed on a likert scale going from 0 (not adopted) to 4

(fully adopted and widely used).¹³ However – given that 2018 still belongs to the initial stage of AI adoption among Spanish companies and the scarce variability observed in scoring – we decided to collapse the information into an overall AI dummy that is equal to 1 if the firm adopted (even at an early stage) at least one of the four aforementioned technologies and zero otherwise.¹⁴

We restrict the sample to firms with non-missing AI information for both 2018 and 2022. Based on this restricted sample, the AI variable indicates that 218 firms (21.5%) used AI in both 2018 and 2022 (always users), while 780 firms (76.9%) did not use AI in either year (never users). 10 firms (0.9%) adopted AI between 2018 and 2022, transitioning from non-use to use (adopters), whereas 7 firms (0.7%) discontinued AI use over the same period (stoppers). Based on these classifications, we construct indicators of AI use for 2018 and 2022.¹⁵

Another valuable insight provided by the ESEE is its sectoral-level analysis (NACE classification). Although we do not observe significant changes between 2018 and 2022, [Figure 1](#) reveals substantial heterogeneity across industries in AI adoption, as expected. The figure also shows that the sectors with the highest rates of AI users are ‘Computer products, electronics and optical’ (52%), ‘Vehicles and accessories’ (38%), ‘Machinery and equipment’ (30%) and ‘Plastic and rubber products’ (30% in 2018 and 29% in 2022). In contrast, the sectors with the lowest AI user rates are ‘Leather, fur and footwear’ (10%), ‘Electric materials and accessories’ (0% in 2018 and 9% in 2022), and ‘Textiles and clothing’ (7% in 2018 and 5% in 2022).¹⁶

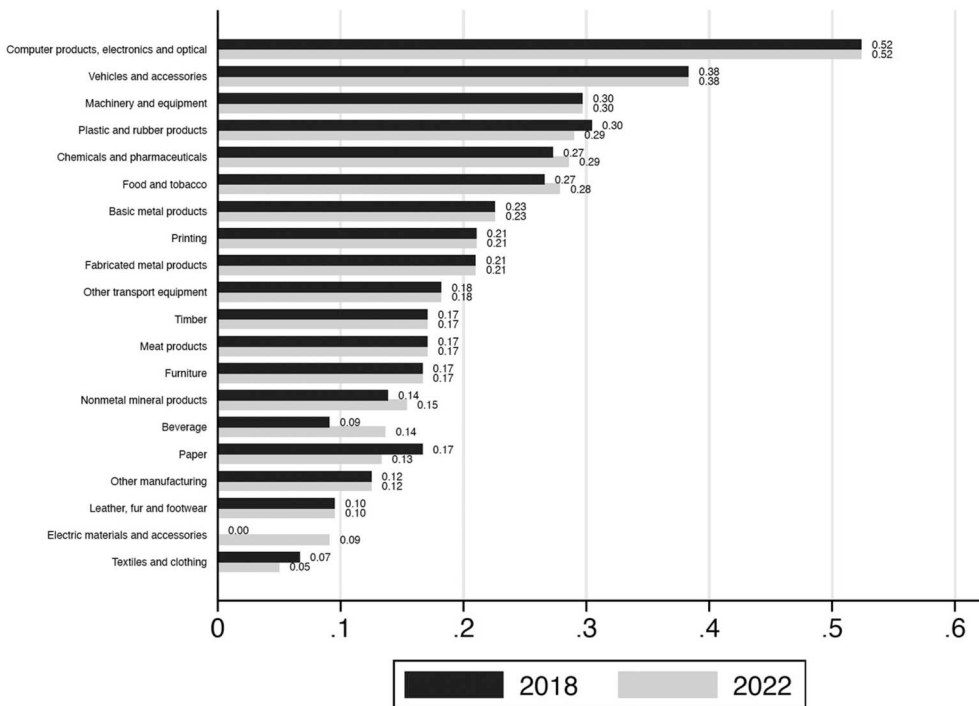


Figure 1. The AI use in 2018 vs 2022 by industries. Note: [Figure 1](#) reports the share of firms using AI in 2018 and 2022, by industry, using the full sample of firms from the ESEE data

Table 1. Descriptive statistics: Non-AI users vs AI users.

	(1) Non-AI use mean/sd	(2) obs	(3) AI use mean/sd	(4) obs	(5) Total mean/sd	(6) obs
R&D	2.83 (5.10)	779	5.759 (6.404)	214	3.461 (5.537)	993
Internal R&D	2.24 (4.679)	779	4.945 (6.197)	214	2.823 (5.163)	993
External R&D	1.679 (3.963)	779	3.668 (5.450)	214	2.108 (4.401)	993
ETC	2.118 (4.640)	750	4.499 (6.348)	203	2.625 (5.142)	953
Employment	4.155 (.838)	790	4.892 (.952)	225	4.318 (.917)	1015
Collwithuni (Dummy)	0.143 (.350)	790	0.32 (.468)	225	0.182 (.386)	1015
% EG	1.891 (1.107)	629	2.306 (.986)	169	1.979 (1.095)	798
TCA (Dummy)	0.011 (.106)	790	0.049 (.216)	225	0.02 (.139)	1015
Foreign	8.678 (27.310)	779	18.112 (38.030)	214	10.711 (30.175)	993
PEURP (Dummy)	0.006 (.079)	790	0.04 (.196)	225	0.014 (.117)	1015
R&D (Dummy)	0.24 (.427)	779	0.458 (.499)	214	0.287 (.453)	993
Internal R&D (Dummy)	0.19 (.393)	779	0.397 (.490)	214	0.235 (.424)	993
External R&D (Dummy)	0.155 (.362)	779	0.322 (.469)	214	0.191 (.394)	993
ETC (Dummy)	0.176 (.381)	750	0.34 (.475)	203	0.211 (.408)	953

Note: The table reports means and standard deviations (in parentheses) of firm-specific variables for three groups: AI non-users (i.e. firms that never use AI in 2018 (Column 1)), AI users (firms that used AI in 2018 (Column 3)), and the full sample (Column 5). R&D refers to total research and development expenditure (internal and external, in logs and dummy) in 2022. Internal R&D and External R&D denote internal and external R&D expenditures, respectively (both in logs and dummy) in 2022. Embodied Technological Change (ETC) is measured as the cost of capital goods purchased for product improvement (in logs and dummy) in 2022. Employment is the total number of employees (in logs) in 2022. Collwithuni captures whether the firm collaborates with universities and/or technology centres (dummy variable) in 2022. % EG represents the percentage of engineers and graduates in the workforce in 2022. TCA indicates the existence of a technological cooperation agreement (dummy variable) in 2022. Foreign refers to the share of foreign ownership (in percent) in 2022. Finally, PEURP measures participation in EU research programmes (dummy variable) in 2022.

Table 1 shows the descriptive statistics of the main variables used in our analysis. The sample is split into two groups: AI non-users and AI users.¹⁷ As can be seen, the means of the innovation inputs (R&D, internal and external R&D, ETC) are higher for AI users than for AI non-users. This provides preliminary evidence of a positive association between AI adoption and innovation inputs. Another interesting finding is that employment is also higher for AI users than for AI non-users, suggesting that – not surprisingly – large companies are more AI-intensive than their smaller counterparts. Other controls beyond the firm's size include (see also Section 4.2): 'Collwithuni' that captures whether the firm collaborates with universities and/or technology centres (dummy variable) in 2022; '% EG', that represents the percentage of engineers and graduates in the workforce in 2022; 'TCA', that indicates the existence of a technological cooperation agreement (dummy variable) in 2022; 'Foreign', that refers to the share of foreign ownership (in percent) in 2022; and 'PEURP', that measures participation in EU research programmes (dummy variable) in 2022.

3.2. The empirical model

In this section, we present the empirical strategy adopted to assess, on the one hand, the complementarity of AI with other innovation activities (specifically R&D – both internal and external – and ETC¹⁸) and, on the other hand, the impact of AI adoption on the subsequent investments in innovation inputs (AI as a Mol).

As far as the complementarity analysis is concerned, we adopt the indirect approach, which assumes that two (or more) activities can be considered complements if their use (or expenditure) tends to move in the same direction, that is, if they are positively correlated. Although this test appears straightforward, the indirect test for complementarity can be biased if the firm's heterogeneity is not adequately considered (Catozzella and Vivarelli 2014). Indeed, many factors, such as the strategies of the companies, their managerial capabilities and the characteristics of the industries influence the innovation activities. To address this issue, Arora and Gambardella (1990) propose estimating conditional rather than unconditional correlations. Specifically, each input is regressed on a set of firm-level and industry-level control variables (Z). The residuals from these regressions are then used to compute the correlation coefficients. A positive and statistically significant correlation among the residuals is interpreted as evidence of complementarity. However, to get consistent estimations, it is necessary to properly compute residuals. In this respect, since internal and external R&D expenditures and ETC are lower-censored at zero, OLS estimators turn out to be inconsistent in this context. To address this issue, we employ Tobit models for these variables. Since AI is observed as a binary variable, we use a probit model for computing AI residuals. Finally, we also use probit models when innovation activities are measured as dummy variables (see Appendix).

To test the hypothesis of AI as a Mol, we estimate the association between the AI and the innovation inputs using the specification outlined in Equation (1). The dependent variables (y_i) are the innovation inputs in 2022: total R&D, internal and external R&D and ETC. The main independent variable is the AI use in 2018, measured as a binary indicator (AI_i).¹⁹

$$y_i = \beta_0 + \beta_1 AI_i + \sum_{k=1}^6 \gamma_k Z_{ik} + v_j + v_r + \epsilon_i \quad (1)$$

We also control for a set of firm-level characteristics (Z_{ik}), including total employment, collaboration with universities and/or technology centres (Collwithuni), the percentage of engineers and graduates in the workforce (% EG), the technological cooperation agreement (TCA), the share of foreign ownership (Foreign) and the participation in EU research programmes (PEURP), all measured in 2022. Equation (1) also contains industry (v_j) and regional (v_r) fixed effects. Finally, ϵ_i is the stochastic error term.

Finally, we investigate potential heterogeneity with regard to firm s' size and sectoral belonging. While the general association between AI and the innovation inputs will be tested through Tobit models when innovation inputs are considered in levels²⁰ and Probit models when inputs are considered as binary variables, the heterogeneity analysis will use OLS. We opt for OLS in this case because it facilitates the analysis of heterogeneity by firm size and technological intensity (i.e. high - vs. low-tech sectors) through the inclusion of interaction terms and the estimation of marginal effects.²¹

4. Results

4.1. Complementarity analysis

In this subsection, we assess complementarity by examining both unconditional and conditional correlations²² among five innovation activities: total R&D, internal and external R&D, Embodied Technological Change (ETC) and Artificial Intelligence (AI) in 2022.

Table 2 presents the unconditional correlation results. These preliminary findings indicate positive and statistically significant correlations among the various innovation activities, suggesting potential complementarities. We also estimate unconditional correlations using binary indicators (see Appendix, Table A1), and the results are consistent with those displayed in Table 2. However, as previously noted, to avoid biased estimates of correlation, it is essential to control for firm – and sector-level characteristics.

We then test the conditional correlation analysis. We adopt the following strategy: first, every innovation input is regressed on a selected set of explanatory variables.²³ Second, we predict the residuals and compute the correlations among them. The results are presented in Table 3: we identify a positive and significant correlation between artificial intelligence and, total and internal R&D (at 90% confidence) and ETC (at 99% confidence). We also estimate conditional correlations using binary indicators (see Appendix, Table A2), and the results are consistent with those presented in Table 3.²⁴ These results provide evidence of complementarity between AI and internal R&D, and between AI and ETC. The loss of significance of the conditional correlation between AI and external R&D possibly reflects the (understandable) prevalent use of in-house AI in enhancing in-house innovation activities (such as internal R&D and ETC), rather than supporting innovative activities conducted externally and out of control.

However, while the detected contemporaneous complementarities are a necessary condition to consider AI as an enabling technology, it is not a sufficient condition. To test whether AI is a Mol, we have to turn our attention to testing the impact of AI on subsequent investments in the various innovative inputs.

4.2. AI as a method of invention

This subsection presents the results of the estimations assessing AI as a Mol. The dependent variables include total R&D, internal and external R&D and ETC. As previously noted, the estimations control for firm-level characteristics: total employment, collaboration with universities and/or technology centres ('Collwithuni'; see Cassiman and Veugelers 2002; Piga and Vivarelli 2003), the proportion of engineers and graduates in the workforce ('%EG'; see Cohen and Levinthal 1990; González, Miles-Touya, and Pazó 2016),

Table 2. Unconditional correlations (levels).

	R&D	Internal R&D	External R&D	ETC	AI 2022
R&D	1				
Internal R&D	0.893***	1			
External R&D	0.772***	0.564***	1		
ETC	0.186***	0.190***	0.179***	1	
AI 2022	0.226***	0.217***	0.201***	0.191***	1
Observations	936				

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3. Conditional correlations (levels).

	R&D	Internal R&D	External R&D	ETC	AI 2022
R&D	1				
Internal R&D	0.867***	1			
External R&D	0.662***	0.389***	1		
ETC	0.0809**	0.116***	0.0845**	1	
AI 2022	0.0659*	0.0756**	0.0441	0.120***	1
Observations	748 ²⁵				

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

technological cooperation agreements ('TCA'; see Iammarino et al. 2012; Zoia et al. 2018), foreign ownership share ('foreign'; see Kwon and Park 2018), and participation in EU research programmes ('PEURP'; see González, Jaumandreu, and Pazó 2005; Pellegrino and Piva 2020). We also include regional and industry fixed effects.

Table 4 presents the results from the Tobit estimations for total R&D, internal and external R&D, and ETC. The findings indicate a positive and significant association between AI and both total and internal R&D, as well as ETC (with the strongest association for ETC). In contrast, the relationship between AI and external R&D is not statistically significant. The control variables present the expected significant coefficients in the case of firm size, scientific collaborations, educated workforce and European programmes. Cooperative agreements and foreign ownership fail to be significant.

Table 5 reports the results from the probit estimations, using binary variables for total, internal, and external R&D, as well as for ETC. The association between AI and the decision to engage in R&D is positive and significant, primarily driven by the positive association

Table 4. The impact of AI on innovation inputs measured in levels – Tobit estimations.

VARIABLES	(1) R&D	(2) Internal R&D	(3) External R&D	(4) ETC
AI 2018	2.791** (1.296)	3.463** (1.494)	1.912 (1.488)	4.641** (1.860)
Employment	1.660*** (0.629)	1.887*** (0.719)	1.395** (0.710)	3.154*** (0.919)
Collwithuni	12.989*** (1.155)	12.715*** (1.345)	15.397*** (1.237)	5.068** (2.060)
% EG	1.925*** (0.594)	2.280*** (0.713)	1.968*** (0.713)	0.956 (0.859)
TCA	-0.468 (2.886)	-0.285 (3.244)	3.124 (3.218)	-2.943 (5.277)
Foreign	-0.012 (0.018)	-0.005 (0.021)	-0.025 (0.021)	-0.066** (0.029)
PEURP	5.310** (2.262)	7.406*** (2.544)	3.477 (3.178)	8.063 (5.490)
Constant	-22.572*** (4.300)	-25.213*** (4.845)	-33.714*** (5.472)	-33.326*** (6.729)
Observations	778	778	778	768

Note: All the dependent variables are in logs. AI 2018 is the use of AI in 2018. Employment is the Log of total number of staff in the company. Collwithuni is the collaboration with universities and/or tech centres (dummy variable). % EG captures the proportion of engineers and graduates. TCA is the technological cooperation agreements (dummy variable). Foreign is the foreign shareholding (%). Finally, PEURP is the participation in EU research programmes (dummy variable). All specifications include regional and industry-fixed effects. Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The reduction in the number of observations in the ETC equation reflects missing values in the dependent variable.

Table 5. The impact of AI on innovation inputs measured as binary variables – Probit estimations.

VARIABLES	(1) R&D	(2) Internal R&D	(3) External R&D	(4) ETC
AI 2018	0.098** (0.046)	0.090** (0.040)	0.043 (0.035)	0.086** (0.038)
Employment	0.045** (0.022)	0.038** (0.019)	0.025 (0.017)	0.057*** (0.019)
Collwithuni	0.464*** (0.055)	0.332*** (0.043)	0.350*** (0.040)	0.095** (0.042)
% EG	0.055*** (0.019)	0.051*** (0.017)	0.040*** (0.015)	0.019 (0.016)
TCA	-0.050 (0.154)	0.002 (0.122)	0.050 (0.103)	-0.067 (0.112)
Foreign	-0.000 (0.001)	0.000 (0.001)	-0.001 (0.000)	-0.001** (0.001)
PEURP	0.396*** (0.141)	0.377*** (0.123)	0.162 (0.128)	0.184 (0.136)
Observations	774	774	754	744

Note: Marginal Effects. All the dependent variables are dummies (Yes or No). AI 2018 is the use of AI in 2018. Employment is the Log of total number of staff in the company. Collwithuni is the collaboration with universities and/or tech centres (dummy variable). % EG captures the proportion of engineers and graduates. TCA is the technological cooperation agreements (dummy variable). Foreign is the foreign shareholding (%). Finally, PEURP is the participation in EU research programmes (dummy variable). All specifications include regional and industry fixed effects. Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The slight reduction in observations for external R&D is due to computational issues affecting the maximum likelihood function used in the probit model, while the reduction in observations in the ETC equation reflects missing values in the dependent variable.

between AI and the decision to invest in internal R&D. Additionally, the results reveal a positive and significant association between AI and the decision to acquire ETC.

Overall, our results show a positive and significant relationship between AI and most of the innovative inputs (in both continuous and binary variable specifications).

In more detail, evidence suggests that AI may favour and accelerate R&D (especially internal ones), probably supporting early-stage experimentation, reducing initial research costs, and improving accuracy and forecasting. The emphasis on internal R&D is particularly relevant as AI might enhance relevance and effectiveness of in-house research investments (so acting as a proper ‘method of invention’). On the other hand, the lack of statistical significance between AI and external R&D is not unexpected: indeed, AI adoption is intended to increase in-house knowledge and internal technological and dynamic capabilities (Tece, Pisano, and Shuen 1997) and not to support innovation activities developed outside the company.

Turning our attention to ETC – which is typically associated with improving production processes through the implementation of innovative machinery, equipment, and software – AI appears to act as a catalyst, boosting ETC adoption (probably through increasing effectiveness, fostering productivity gains and minimizing technical breakdowns). In this respect, AI works more as an enabler of downstream adoption, rather than as a proper ‘method of invention’.

On the whole, AI seems to be fostering the ‘exploitation’ of the in-house innovative resources (both in terms of internal R&D and adoption of embodied technical change) rather than accelerating the ‘exploration’ of new avenues of innovation through external R&D. In other words, our results support a role of AI in ‘deepening’ firm’s innovation, rather than fostering the firm’s ‘widening’ innovation (for a deeper analysis of this

distinction in the economics of innovation, see Fauchart and Keilbach 2009; Greve 2007; Swift 2016). In this respect, our outcomes are consistent with the ones obtained by Bianchini, Müller, and Pelletier (2022) with regard to the role of AI as a ‘method of invention’ in science: indeed, the authors found evidence in favour of AI as a powerful tool in enforcing knowledge capabilities within a given ‘comfort zone’, rather than a lever to explore distant knowledge places and radically rearrange the overall knowledge landscape. This is why the authors put forward a moderate conclusion in which AI is considered an *emerging general method of invention* (Bianchini, Müller, and Pelletier 2022, 12).

4.3. Heterogeneity

In this subsection, we explore the possible heterogeneities in the relationship between firm *s*’ AI adoption and the subsequent investments in innovation inputs. In order to insert the relevant interaction variables and to correctly interpret the estimated coefficients, we estimate linear regression models (OLS²⁶) and include the interactive terms between AI and size (large vs small companies)²⁷ as well as between AI and technological intensity (high-tech vs low-tech sectors).²⁸ After estimating the models, we compute the marginal effects to quantify the relationship and assess whether significant differences emerge across firm size and technological level.²⁹

Table 6 displays the results for the values in levels of the dependent variables (see Panel A) and their categorical values (see Panel B). The results suggest a positive association between AI and total R&D, primarily driven by internal R&D, in large companies. Furthermore, AI is positively associated with ETC in large companies. The results for the categorical values follow the same direction as the previous ones.

Conversely – although the coefficient displays the expected signs – our models do not find significant evidence regarding the enhancing role of AI in the case of small companies. These findings have important implications. Large companies mainly drive the revealed association between AI and innovation inputs, and this may be due to

Table 6. The impact of AI on innovation input by size (OLS).

	(1)	(2)	(3)	(4)
Panel A: Dependent variables in levels				
	R&D	Internal R&D	External R&D	ETC
AI use in Small	0.350 (0.694)	0.624 (0.671)	0.122 (0.482)	0.445 (0.776)
AI use in Large	1.365** (0.665)	1.185* (0.659)	0.627 (0.574)	1.799** (0.735)
Panel B: Binary dependent variables				
	R&D	Internal R&D	External R&D	ETC
AI use in Small	0.037 (0.061)	0.069 (0.059)	0.020 (0.047)	0.038 (0.064)
AI use in Large	0.105** (0.053)	0.093* (0.053)	0.053 (0.050)	0.123** (0.057)
Observations	778	778	778	768
Obs in Small	418			
Obs in Large	360			

Note: All the dependent variables are in logs in Panels A, while all in Panel B are dummies (Yes or No). AI is the use of AI in 2018. The specification contains control variables: employment, collaboration with universities and/or tech centres (dummy variable), the proportion of engineers and graduates, technological cooperation agreements (dummy variable), foreign shareholding (%), and participation in EU research programmes (dummy variable). All specifications include regional and industry-fixed effects. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

different factors. Large companies have the absorptive capacity, the dynamic capabilities and the financial resources to assimilate new AI technologies, while small companies often face major financial constraints and do not have enough capabilities to fully assimilate the latest technologies and get synergies. In contrast, large companies can benefit more from AI adoption since they rely on internal capabilities and organizational structures that enable them to make more value from AI adoption and envisage the possible positive synergy between AI and internal R&D activities. Similarly, ETC is positively associated with AI only in large companies. This is likely due to what was discussed above and to their large-scale production structures, which are better positioned to exploit AI-driven efficiency gains.³⁰

Finally, the results for the high- and low-tech industries³¹ are put forward in Table 7. The results suggest a positive association of AI with total R&D, internal and external R&D in the high-tech sectors, while the association of AI with ETC is positive and significant in the low-tech industries (while not significant in the other three cases³²). The consistent positive relationships between AI adoption and R&D in high-tech industries likely reflect these firms' greater propensity to invest in innovation activities, supported by the presence of R&D departments and the innovative nature of their competitive environment. In this context, AI adoption appears to be an accelerator of all the knowledge-intensive activities, including – in this case – external R&D, as well.

Conversely, firms operating in low-tech sectors appear to significantly benefit from AI through an enhanced access to ETC, which is the dominant channel of technological advancement in the most traditional manufacturing industries. In these sectors, AI adoption is probably conceived as a tool to make technological acquisition more fruitful.

Clearly enough, another important source of heterogeneity is generated by the specific roles played by the single technologies which contribute to build our aggregated AI indicator (see Section 3.1). In this respect, we tentatively estimated our specification using dummies for the single AI technologies, instead of our overall AI indicator. What emerges is a driver role of machine learning, data-driven management and big data

Table 7. The impact of AI on innovation input by technological intensity (OLS).

	(1)	(2)	(3)	(4)
Panel A: Dependent variables in levels				
	R&D	Internal R&D	External R&D	ETC
AI use in Low-tech	0.616 (0.563)	0.660 (0.547)	-0.052 (0.444)	1.933*** (0.652)
AI use in High-tech	1.949** (0.949)	1.791* (0.965)	1.679** (0.844)	-0.284 (0.981)
Panel B: Binary dependent variables				
	R&D	Internal R&D	External R&D	ETC
AI use in Low-tech	0.045 (0.046)	0.055 (0.045)	-0.000 (0.039)	0.144*** (0.051)
AI use in High-tech	0.168** (0.077)	0.158** (0.078)	0.142* (0.075)	-0.040 (0.077)
Observations	778	778	778	768
Obs Low-tech	594			
Obs High-tech	184			

Note: All the dependent variables are in logs in Panels A, while all in Panel B are dummies (Yes or No). AI is the use of AI in 2018. The specification contains control variables: employment, collaboration with universities and/or tech centres (dummy variable), the proportion of engineers and graduates, technological cooperation agreements (dummy variable), foreign shareholding (%), and participation in EU research programmes (dummy variable). All specifications include regional and industry-fixed effects. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

(results are available upon request). However, this outcome should be taken with extreme caution, since the analysis is severely limited by the paucity of positive observations for each AI technology and therefore scarce variability in the data (see also the discussion in Section 3.1 above).

5. Conclusions

Artificial Intelligence, with its pervasive influence on economies and societies, is reshaping how firms innovate and produce. Its rapid diffusion and large application require attention to fully comprehend risks, effects and consequences. While the existing empirical evidence, using various proxies to operationalize AI, increasingly points to AI as a driver of productivity and economic growth, less is known about how AI affects conventional innovation activities and whether complementarities among AI and innovative inputs exist. However, if AI is considered not only a General Purpose Technology, but also a Method of Invention, understanding its interaction with firm's innovation strategies is essential.

This study contributes to this debate by analysing firm-level data from the Spanish manufacturing sector. It explores two key questions: (1) whether AI complements R&D and other innovation inputs, specifically Embodied Technological Change; (2) whether AI can be considered as a MoI, fostering subsequent investments in innovation inputs. Results (1) show a robust correlation between AI adoption and internal R&D and between AI adoption and ETC (both in a conditional and an unconditional framework), suggesting a certain degree of complementarity; (2) highlight, in a dynamic perspective, a general positive and significant impact of AI on internal R&D (pointing to AI as a proper 'method of invention') and ETC (pointing to AI as a facilitator of innovative adoption), suggesting that AI may trigger and amplify internal innovation investments. In contrast, AI does not exhibit a significant impact on external R&D, confirming AI as an emergent method of invention (Bianchini, Müller, and Pelletier 2022): for the time being, AI is mainly used as a deepening tool rather than an explorative one.

Our findings also reveal heterogeneity across firms. Indeed, our two main results (AI fostering internal R&D and ETC) seem to be driven by larger firms, likely able to better envisage and value the synergic potentialities of AI adoption. Finally, splitting by industries, companies in high-tech sectors seem to benefit more from AI in their R&D departments, while firms in more traditional industries exploit AI in increasing their acquisition of ETC.

These results may have important policy implications: promoting AI adoption might have a booster effect on different innovation activities acting both as a catalyst and an accelerator. Yet, policy-makers should also be aware of a significant degree of heterogeneity across industries and across firm's size (implying the need for targeted industrial and innovation policies).

From a managerial perspective, evidence suggests that AI adoption can foster innovation propensity. However, as highlighted by Bianchini, Müller, and Pelletier (2022) and Antonioli et al. (2024), in-house dynamic capabilities, human capital endowment, and organizational change might be important mediators of what is discussed in this study.

The lack of data on these latter dimensions is one of the limitations of this paper; moreover, dealing with contemporaneous correlations and with four-year-span regressions

prevents us from inferring any causal effect; finally, while the Spanish case offers valuable insights, country-specific factors, including sectoral and national AI and innovation supporting schemes, may influence the generalizability of our results.³³

As far as future avenues of research are concerned, a more holistic approach might investigate the overall interactions among AI, the innovative inputs (used in this study as dependent variables), the collaborations between the focal firm and external innovative agents (used in this study as controls) and other innovative characteristics of the focal firm (such as, for instance, its absorptive capacity, see Cohen and Levinthal 1990). In this respect, longitudinal data beyond the ESEE dataset used in this study would be precious.

Notes

1. For more information about the SEPI Foundation and ESEE data, please refer to www.fundacionsepi.es
2. In particular, the ESEE offers insights into AI applications in the following areas: (1) 'automatically guided vehicles or systems (self-driving vehicles, drones)'; (2) 'machine learning / data driven management / big data'; (3) 'computer/machine vision'; and (4) 'natural language processing'.
3. To illustrate this point, one can consider the pharmaceutical sector. When a laboratory seeks to discover and develop a new drug, AI plays an increasingly important role by accelerating the identification of synthesizable molecules, nucleic acid sequences, and proteins with specific structures or functions. In doing so, it enhances both the efficiency (in terms of time and cost) and the effectiveness of drug development (Vert 2023).
4. Coccia (2019) provides a compelling example of this: the use of AI, particularly deep learning, can assist pathologists in detecting cancer subtypes, gene mutations, and/or metastases, thereby enabling the application of appropriate therapies.
5. To enhance AI's potential, firms need to understand how quickly AI will impact their sector, recognize its exponential progress, and manage the feedback in a continuous learning loop. However, concerns about negative effects and risks of AI have sparked policy debates, including a 2023 petition calling for a pause in AI research. Goldfarb (2024), analysing those concerns, underlines a long-term optimism about AI's transformative potential while acknowledging short-term risks.
6. In Section 4, complementarities will be tested using unconditional and conditional correlations, following the empirical approach inspired by Milgrom and Roberts and subsequent literature. However, a full structural test of supermodularity will not be implemented, as this paper does not focus on estimating an innovation production function (Griliches 1957).
7. One specific case is 'Generative AI' which refers to AI models that are specifically designed to produce content, like text, programme codes, images, videos, or sounds, in response to human language queries or prompts. This tool utilizes Large Language Models (LLMs) and requires a substantial amount of data, employing algorithms to predict responses. The Generative AI can transform innovation in boosting idea generation, increasing individual creativity and rendering more effective the R&D investments (Calvino, Reijerink, and Samek 2025).
8. Both studies use a survey-based approach, collecting data through questionnaires conducted in the United States and Colombia, respectively.
9. More recently, ESEE data have been used to explore the impact of ETC on employment (Pellegriño, Piva, and Vivarelli 2019), to measure the microeconomic implications of robot adoptions (Koch, Manuylov, and Smolka 2021), and to examine the role of robot adoption on product innovation (Antonioli et al. 2024).
10. The question asks to the companies in 2018 and 2022: to what extent did your company use the following Industry 4.0 technologies in the production, marketing, or distribution of its products and services? (Select one option for each technology): Augmented/Virtual Reality;

Cyber-physical systems; Automatically guided vehicles (e.g., autonomous vehicles, drones); Automated storage and retrieval systems; Machine learning / Data-driven management / Big data; Cloud computing; Computer vision/machine vision; Natural language processing; RFID-based identification and inventory systems; Industrial robotics, Touchscreens/kiosks for client interface; IoT / IIoT (Internet of Things / Industrial IoT); 3D printing / Additive manufacturing

11. The innovation inputs are: total R&D, internal R&D, external R&D and ETC.
12. Spain's national and regional policies over the investigated period 2018–2022, including PIC 4.0, ENIA, and regional digital strategies (Eurofound, 2022), have aimed at providing partial financial and infrastructural support for AI adoption. By 2022, these coordinated incentives likely enabled firms to implement AI technologies more effectively, though adoption varied across regions. However, similar policy approaches were also implemented in other European economies (see Ricart et al. 2022), suggesting that, while the Spanish case may not be generalizable, it shares common elements with a broader international AI and digital innovation policy strategy. To take the European policy dimension into account, we included the PEURP dummy in our estimates and – to capture regional specificities – we included regional dummies in all the proposed specifications (see *infra*).
13. Indeed, we tried to implement the number of implemented AI technologies (from 0 to 4) as a distinct regressor in our subsequent econometric analysis, with no significant results; therefore we cannot assess the potential important role of the intensive margin in AI adoption. Instead, in the following Section 4.3 we will tentatively investigate the role of the single AI technologies.
14. In addition, using an AI dummy simplifies interpretation and mitigates a potential issue of paucity of positive observations (see the next paragraph).
15. Specifically, firms classified as stoppers are included among the AI users in 2018, while adopters are included among the AI users in 2022. In 2018, 22.2% of firms used AI, while 77.8% did not. In 2022, the proportion of AI users increased slightly to 22.5%, with non-users accounting for 77.5%. The total sample for the AI variable consists of 1,015 firms. In 2018, 225 firms were classified as AI users and 790 as non-users. In 2022, the number of AI users was 228, while the number of non-users was 787.
16. Our final sample shows that 22,5% of firms have adopted AI in 2022. This figure is broadly consistent with the 27% reported by the Strand Partners study (2024) for Spain as well as with evidence from a comparative analysis of 11 OECD countries proposed by Calvino and Fontanelli (2023). However, it is higher than the 9,6% of Spanish firms adopting AI in 2022, as reported in the 'Survey on ICT and Electronic Commerce Use in Companies' (INE 2023), where large companies (≥ 250 employees) display a figure of approx. 40%, while medium firms (50–249) 17%, and small companies (10–49) 6%. This discrepancy reflects the still evolving heterogeneous nature of AI adoption and the challenges associated with its measurement. In our case, the available data are characterized by a relatively high share of large firms, which are more likely to adopt AI and more likely to remain in the panel over time. Although this might introduce a size-related bias, the statistical evidence on the sectoral distribution of AI adoption in our sample is consistent with the OECD (2026) findings for Spain related to 2023. In particular, in the OECD study the information and technology sector shows the highest adoption rate, with nearly 45% of firms adopting AI in 2023, compared to the 52% in the computer products sector in our sample (see Figure 1).
17. We focus on AI use in 2018, as our regression analysis examines the impact of AI adoption in 2018 on innovation inputs in 2022. Descriptive statistics for AI users in 2022 yield similar results and are available upon request.
18. ETC is basically the investment in innovative plants, machinery, and equipment (Catozzella and Vivarelli 2014) and it is considered a proxy for process innovation (Pellegrino, Piva, and Vivarelli 2019).
19. The four year lag between the dependent variable and the AI indicator mitigates possible endogeneity issues; however, data limitations prevent us from any casual interpretation of our findings. Moreover, the unavailability of previous information about the companies adopting AI in 2018 does not allow us to control for possible sample selection.

20. A Tobit model is used due to the high incidence of zero values in the dependent variables (innovation inputs).
21. To compute the marginal effects, it is necessary to introduce an interaction term in Equation (1): $y_i = \beta_0 + \beta_1 AI_i + \beta_2 Size_i + \varphi(AI_i * Size_i) + \sum_{k=1}^6 \gamma_k Z_{ik} + v_j + v_i + \epsilon_i$ where $Size_i$ is a dummy variable equal to one if the firm is large, and zero otherwise. After estimating the equation, we compute the marginal effect of AI_i as: $\delta y_i / \delta AI_i = \beta_1 + \varphi Size_i$. This leads to two cases: if $Size = 1$ (large firms), then $\delta y_i / \delta AI_i = \beta_1 + \varphi$ and $Size = 0$ (small firms) then $\delta y_i / \delta AI_i = \beta_1$. The same holds for the case of technological intensity (high and low-tech sectors).
22. As already clarified in Section 2, we do not perform a full structural test of supermodularity.
23. The control variables are employment, collaboration with universities and/or tech centres, proportion of engineers and graduates, technological cooperation agreements, foreign shareholding, participation in EU research programmes, regions, and industry fixed-effects
24. In both this correlation analysis and in the following regression estimates, we display results using binary indicators (0/1) of the relevant variables with two purposes in mind: 1) to provide a robustness check, to be compared with results based on the tobit methodology; 2) to give account of the relationships which may affect the decisions to invest or not invest in the different innovation inputs.
25. The smaller number of observations in the conditional correlation analysis is attributable to missing values in the control variables.
26. We opted for a OLS methodology – instead of the Tobit and Probit settings used in the benchmark estimations – since cross terms and marginal effects of interactions are very difficult to interpret within non-linear frameworks. However, for sake of coherence, we also replicated the estimations displayed in Tables 6 and 7 using Tobit and Probit specifications and results (available upon request) are overall fully consistent, with the sole exception of a lack of significance with regard to the tobit regressions for the high-tech industries.
27. To split the sample, we use the median value of employment, which is 72 employees.
28. The classification between high – and low-tech sectors is presented in Table A.3 in the Appendix and is based on the OECD classification. For more detail, see Hatzichronoglou (1997).
29. Dealing with subsamples obtained by an overall sample of 778 firms may raise an issue of statistical power of the proposed regressions. Therefore, the results discussed in this section should be considered as suggestive.
30. It is worth remembering that only manufacturing companies are included in our sample.
31. For more details regarding our classification, see Table A.3.
32. Notice that this is not a direct consequence of paucity of observations, since low-tech companies represent the majority of our sample (see the numbers reported at the bottom of Table 7).
33. See FN 12.

Author contributions

CRediT: **Guillermo Arenas Díaz**: Methodology; **Mariacristina Piva**: Validation; **Marco Vivarelli**: Conceptualization.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

Marco Vivarelli and Mariacristina Piva acknowledge the support by the Italian Ministero dell'Università e della Ricerca – MUR (PRIN-2022, project 2022P499ZB: 'Innovation and labor market dynamics'; principal investigator: Marco Vivarelli; funded by the European Union – Next Generation EU). The

views and opinions expressed are only those of the authors and do not necessarily reflect those of the European Union or the European Commission. Neither the European Union nor the European Commission can be held responsible for them.

References

- Acemoglu, D., D. H. Autor, J. Hazell, and P. Restrepo. 2022. "Artificial Intelligence and Jobs: Evidence from Online Vacancies." *Journal of Labor Economics* 40 (S1): S293–S340. <https://doi.org/10.1086/718327>.
- Aghion, P., B. F. Jones, and C. I. Jones. 2017. Artificial Intelligence and Economic Growth. National Bureau of Economic Research, *NBER Working Papers* 23928.
- Agrawal, A., J. Gans, and A. Goldfarb, eds. 2019. *The Economics of Artificial Intelligence: An Agenda*. Chicago: University of Chicago Press.
- Agrawal, A., J. S. Gans, and A. Goldfarb. 2024. "Artificial Intelligence Adoption and System-Wide Change." *Journal of Economics & Management Strategy* 33:327–337. <https://doi.org/10.1111/jems.12521>.
- Antonioni, D., A. Marzucchi, F. Rentocchini, and S. Vannuccini. 2024. "Robot Adoption and Product Innovation." *Research Policy* 53(6):105002. <https://doi.org/10.1016/j.respol.2024.105002>.
- Arora, A., and A. Gambardella. 1990. "Complementarity and External Linkages: The Strategies of the Large Firms in Biotechnology." *The Journal of Industrial Economics* 38(4):361–379. <https://doi.org/10.2307/2098345>.
- Babina, T., A. Fedykc, A. Hed, and J. Hodson. 2024. "Artificial Intelligence, Firm Growth, and Product Innovation." *Journal of Financial Economics* 151:103745. <https://doi.org/10.1016/j.jfineco.2023.103745>.
- Batabyal, A. A., K. Kourtit, and P. Nijkamp. 2025. "Artificial Intelligence Based Technologies and Economic Growth in a Creative Region." *Economics of Innovation and New Technology* 34:782–796. <https://doi.org/10.1080/10438599.2024.2374273>.
- Bianchini, S., M. Müller, and P. Pelletier. 2022. "Artificial Intelligence in Science: An Emerging General Method of Invention." *Research Policy* 51(10):104604. <https://doi.org/10.1016/j.respol.2022.104604>.
- Bocquet, R., O. Brossard, and M. Sabatier. 2007. "Complementarities in Organizational Design and the Diffusion of Information Technologies: An Empirical Analysis." *Research Policy* 36(3):367–386. <https://doi.org/10.1016/j.respol.2006.12.005>.
- Bresnahan, T. F., and M. Trajtenberg. 1995. "General Purpose Technologies 'Engines of Growth?'" *Journal of Econometrics* 65(1):83–108. [https://doi.org/10.1016/0304-4076\(94\)01598-T](https://doi.org/10.1016/0304-4076(94)01598-T).
- Brunetti, I., S. Dughera, and A. Ricci. 2025. "Technological Path-Dependency in AI Adoption: Evidence from Italian Firms." *Economics of Innovation and New Technology* 1–22. <https://doi.org/10.1080/10438599.2025.2573062>.
- Brynjolfsson, E., D. Rock, and C. Syverson. 2019. "Artificial Intelligence and the Modern Productivity Paradox: A Clash of Expectations and Statistics." In *The Economics of Artificial Intelligence: An Agenda*, edited by A. Agrawal, J. Gans, and A. Goldfarb, 23–60. University of Chicago Press, Chicago.
- Calvino, F., and L. Fontanelli. 2023. A Portrait of AI Adopters Across Countries: Firm Characteristics, Assets' Complementarities and Productivity. OECD Science, Technology and Industry Working Papers 2023/02, OECD Publishing. <https://doi.org/10.1787/0fb79bb9-en>
- Calvino, F., J. Reijerink, and L. Samek. 2025. The Effects of Generative AI on Productivity, Innovation and Entrepreneurship. *OECD Artificial Intelligence Papers*, No. 39, OECD Publishing. <https://doi.org/10.1787/b21df222-en>
- Cassiman, B., and R. Veugelers. 2002. "R&D Cooperation and Spillovers: Some Empirical Evidence from Belgium." *American Economic Review* 92(4):1169–1184. <https://www.jstor.org/stable/3083305>.
- Catozzella, A., and M. Vivarelli. 2014. "The Catalysing Role of in-house R&D in Fostering Complementarity among Innovative Inputs." *Industry and Innovation* 21(3):179–196. <https://doi.org/10.1080/13662716.2014.910890>.
- Coccia, M. 2019. "Artificial Intelligence Technology in Cancer Imaging: Clinical Challenges for Detection of Lung and Breast Cancer." *Journal of Social and Administrative Sciences* 6 (2):82–98. <https://doi.org/10.1453/jsas.v6i2.1888>.

- Cockburn, I. M., R. Henderson, and S. Stern. 2019. "The Impact of Artificial Intelligence on Innovation: An Exploratory Analysis." In *The Economics of Artificial Intelligence: An Agenda*, edited by A. Agrawal, J. Gans, and A. Goldfarb, 115–148. Chicago: University of Chicago Press.
- Cohen, W., and D. Levinthal. 1990. "Absorptive Capacity: A new Perspective on Learning and Innovation." *Administrative Science Quarterly* 35 (1):128–152. <https://www.jstor.org/stable/2393553>.
- Damioli, G., V. Van Roy, and D. Vertesy. 2021. "The Impact of Artificial Intelligence on Labor Productivity." *Eurasian Business Review* 11(1):1–25. <https://doi.org/10.1007/s40821-020-00172-8>.
- Damioli, G., V. Van Roy, D. Vertesy, and M. Vivarelli. 2024. "Drivers of Employment Dynamics of AI Innovators." *Technological Forecasting and Social Change* 201:123249. <https://doi.org/10.1016/j.techfore.2024.123249>.
- Damioli, G., V. Van Roy, D. Vertesy, and M. Vivarelli. 2025. "Is Artificial Intelligence Leading to a New Technological Paradigm?" *Structural Change and Economic Dynamics* 72:347–359. <https://doi.org/10.1016/j.strueco.2024.12.006>.
- Eurofound. 2022. *Connected Industry 4.0, measure ES-2016-28/2697 (measures in Spain)*. EU PolicyWatch, Dublin. https://static.eurofound.europa.eu/covid19db/cases/ES-2016-28_2697.html.
- Fauchart, E., and M. Keilbach. 2009. "Testing a Model of Exploration and Exploitation as Innovation Strategies." *Small Business Economics* 33(3):257–272. <https://doi.org/10.1007/s11187-008-9101-6>.
- Felten, E. W., M. Raj, and R. Seamans. 2021. "Occupational, Industry, and Geographic Exposure to Artificial Intelligence: A Novel Dataset and Its Potential Uses." *Strategic Management Journal* 42 (12): 2195–2217. <https://doi.org/10.1002/smj.3286>.
- Freeman, C., J. Clark, and L. Soete. 1982. *Unemployment and Technical Innovation*. London: Pinter.
- Fujii, H., and S. Managi. 2018. "Trends and Priority Shifts in Artificial Intelligence Technology Invention: A Global Patent Analysis." *Economic Analysis and Policy* 58:60–69. <https://doi.org/10.1016/j.eap.2017.12.006>.
- García-Quevedo, J., G. Pellegrino, and M. Vivarelli. 2014. "R&D Drivers and Age: Are Young Firms Different?" *Research Policy* 43 (9):1544–1556. <https://doi.org/10.1016/j.respol.2014.04.003>.
- Ghasemaghaei, M., and G. Calic. 2019. "Does big Data Enhance Firm Innovation Competency? The Mediating Role of Data-Driven Insights." *Journal of Business Research* 104:69–84. <https://doi.org/10.1016/j.jbusres.2019.07.006>.
- Goldfarb, A. 2024. "Pause Artificial Intelligence Research? Understanding AI Policy Challenges." *Canadian Journal of Economics/Revue Canadienne D'économique* 57:363–377. <https://doi.org/10.1111/caje.12705>.
- González, X., J. Jaumandreu, and C. Pazó. 2005. "Barriers to Innovation and Subsidy Effectiveness." *RAND Journal of Economics* 36 (4):930–950. <https://www.jstor.org/stable/4135264>.
- González, X., D. Miles-Touya, and C. Pazó. 2016. "R&D, Worker Training and Innovation: Firm-Level Evidence." *Industry and Innovation* 23(8):694–712. <https://doi.org/10.1080/13662716.2016.1206463>.
- Greenan, N., D. Guarascio, and J. Reljic. 2025. "AI and the Labour Market: Opening the Black box." *Eurasian Business Review* 15(4):925–951. <https://doi.org/10.1007/s40821-025-00324-8>.
- Greve, H. R. 2007. "Exploration and Exploitation in Product Innovation." *Industrial and Corporate Change* 16(5):945–975. <https://doi.org/10.1093/icc/dtm013>.
- Griliches, Z. 1957. "Hybrid Corn: An Exploration in the Economics of Technological Change." *Econometrica* 25(4):501–522. <https://doi.org/10.2307/1905380>.
- Hatzichronoglou, T. 1997. Revision of the High-Technology Sector and Product Classification. *OECD Science, Technology and Industry Working Papers No. 1997/02*, Paris.
- Holm, J. R., D. S. Hain, R. Jurowetzki, and E. Lorenz. 2023. "Innovation Dynamics in the Age of Artificial Intelligence: Introduction to the Special Issue." *Industry and Innovation* 30(9):1141–1155. <https://doi.org/10.1080/13662716.2023.2272724>.
- Iammarino, S., M. Piva, M. Vivarelli, and N. Von Tunzelmann. 2012. "Technological Capabilities and Patterns of Innovative Cooperation of Firms in the UK Regions." *Regional Studies* 46(10):1283–1301. <https://doi.org/10.1080/00343404.2012.679259>.

- INE. 2023. Survey on ICT and Electronic Commerce Use in Companies. Instituto Nacional de Estadística. https://www.ine.es/dyngs/INEbase/en/categoria.htm?c=Estadistica_P&cid=1254735976151.
- Koch, M., I. Manuylov, and M. Smolka. 2021. "Robots and Firms." *The Economic Journal* 131(638):2553–2584. <https://doi.org/10.1093/ej/ueab009>.
- Kwon, H. U., and J. Park. 2018. "R&D, Foreign Ownership, and Corporate Groups: Evidence from Japanese Firms." *Research Policy* 47(2):428–439. <https://doi.org/10.1016/j.respol.2017.11.010>.
- Lábaj, M., T. Oleš, and G. Procházka. 2025. "Impact of Robots and Artificial Intelligence on Labor and Skill Demand: Evidence from the UK." *Eurasian Business Review* 15(4):953–1001. <https://doi.org/10.1007/s40821-025-00314-w>.
- Liu, J., H. Chang, J. Y.-L. Forrest, and B. Yang. 2020. "Influence of Artificial Intelligence on Technological Innovation: Evidence from the Panel Data of China's Manufacturing Sectors." *Technological Forecasting and Social Change* 158:120142. <https://doi.org/10.1016/j.techfore.2020.120142>.
- Lozada, N., J. Arias-Pérez, and G. Perdomo-Charry. 2019. "Big Data Analytics Capability and co-innovation: An Empirical Study." *Heliyon* 5(10):e02541. <https://doi.org/10.1016/j.heliyon.2019.e02541>.
- Mariani, M. M., I. Machado, and S. Nambisan. 2023. "Types of Innovation and Artificial Intelligence: A Systematic Quantitative Literature Review and Research Agenda." *Journal of Business Research* 155:113364. <https://doi.org/10.1016/j.jbusres.2022.113364>.
- Milgrom, P., and J. Roberts. 1990. "The Economics of Modern Manufacturing: Technology, Strategy, and Organization." *American Economic Review* 80 (3):511–528. <https://www.jstor.org/stable/2006681>.
- Milgrom, P., and J. Roberts. 1995. "Complementarities and fit Strategy, Structure, and Organizational Change in Manufacturing." *Journal of Accounting and Economics* 19 (2–3): 179–208. [https://doi.org/10.1016/0165-4101\(94\)00382-F](https://doi.org/10.1016/0165-4101(94)00382-F).
- Miller, T. 2019. "Explanation in Artificial Intelligence: Insights from the Social Sciences." *Artificial Intelligence* 267:1–38. <https://doi.org/10.1016/j.artint.2018.07.007>.
- Mohnen, P., and L. H. Röller. 2005. "Complementarities in Innovation Policy." *European Economic Review* 49(6):1431–1450. <https://doi.org/10.1016/j.euroecorev.2003.12.003>.
- Montobbio, F., J. Staccioli, M. E. Virgillito, and M. Vivarelli. 2024. "Labour-Saving Automation: A Direct Measure of Occupational Exposure." *The World Economy* 47(1):332–361. <https://doi.org/10.1111/twec.13522>.
- Niebel, T., F. Rasel, and S. Viète. 2019. "Big Data – Big Gains? Understanding the Link Between Big Data Analytics and Innovation." *Economics of Innovation and New Technology* 28(3):296–316. <https://doi.org/10.1080/10438599.2018.1493075>.
- OECD. 2024. Explanatory Memorandum on the Updated OECD Definition of an AI system. <https://doi.org/10.1787/623da898-en>
- OECD. 2026. OECD ICT Access and Usage Database. <https://goingdigital.oecd.org/datakitchen/#/cover/5/ict/indicator/explore/en>.
- Pellegrino, G., and M. Piva. 2020. "Innovation, Industry and Firm Age: Are There New Knowledge Production Functions?" *Eurasian Business Review* 10(1):65–95. <https://doi.org/10.1007/s40821-019-00129-6>.
- Pellegrino, G., M. Piva, and M. Vivarelli. 2019. "Beyond r&d: The Role of Embodied Technological Change in Affecting Employment." *Journal of Evolutionary Economics* 29(4):1151–1171. <https://doi.org/10.1007/s00191-019-00635-w>.
- Piga, C., and M. Vivarelli. 2003. "Sample Selection in Estimating the Determinants of Cooperative R&D." *Applied Economics Letters* 10(4):243–246. <https://doi.org/10.1080/1350485022000044156>.
- Rammer, C., G. P. Fernández, and D. Czarnitzki. 2022. "Artificial Intelligence and Industrial Innovation: Evidence from German Firm-Level Data." *Research Policy* 51(4):104555. <https://doi.org/10.1016/J.RESPOL.2022.104555>.
- Ricart, J. R., V. Van Roy, F. Rossetti, and L. Tangi. 2022. *AI Watch - National Strategies on Artificial Intelligence: A European Perspective*. 2022 ed. Luxembourg: Publications Office of the European Union. <https://doi.org/10.2760/385851>
- Salter, W. E. G. 1960. *Productivity and Technical Change*. Cambridge: Cambridge University Press.

- Sjödín, D., V. Parida, M. Palmié, and J. Wincent. 2021. "How AI Capabilities Enable Business Model Innovation: Scaling AI through Co-evolutionary Processes and Feedback Loops." *Journal of Business Research* 134:574–587. <https://doi.org/10.1016/j.jbusres.2021.05.009>.
- Solow, R. M. 1960. "Investment and Technical Progress." In *Mathematical Methods in the Social Sciences*, edited by K. J. Arrow, S. Karlin, and P. Suppes, 89–104. Stanford: Stanford University Press.
- Strand Partners. 2024. Unlocking Spain's AI Ambitions in the Digital Decade: Spain Report. AWS. https://www.unlockingeuropesaipotential2024.com/_files/ugd/c4ce6f_d315aad72b0a4f8ea1555a429130898c.pdf.
- Stucki, T., and D. Wochner. 2019. "Technological and Organizational Capital: Where Complementarities Exist." *Journal of Economics & Management Strategy* 28(3):458–487. <https://doi.org/10.1111/jems.12269>.
- Swift, T. 2016. "The Perilous Leap between Exploration and Exploitation." *Strategic Management Journal* 37(8):1688–1698. <https://doi.org/10.1002/smj.2423>.
- Teece, D. J., G. Pisano, and A. Shuen. 1997. "Dynamic Capabilities and Strategic Management." *Strategic Management Journal* 18(7):509–533. [https://doi.org/10.1002/\(SICI\)1097-0266\(199708\)18:7<509::AID-SMJ882>3.0.CO;2-Z](https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z).
- Triguero, A., D. Córcoles, and M. C. Cuerva. 2014. "Persistence of Innovation and Firm's Growth: Evidence from a Panel of SME and Large Spanish Manufacturing Firms." *Small Business Economics* 43:787–804. <https://doi.org/10.1007/s11187-014-9562-8>.
- Vahter, P., and M. Vadi. 2024. "The Relationship of Technological and Organizational Innovation with Firm Performance: Opening the Black box of Dynamic Complementarities." *Technological Forecasting and Social Change* 206:123516. <https://doi.org/10.1016/j.techfore.2024.123516>.
- Vert, J.-P. 2023. "How Will Generative AI Disrupt Data Science in Drug Discovery?" *Nature Biotechnology* 41(6):750–751. <https://doi.org/10.1038/s41587-023-01789-6>.
- Yogesh, K. D., L. Hughes, E. Ismagilova, G. Aarts, C. Coombs, T. Crick, Y. Duan, et al. 2021. "Artificial Intelligence (AI): Multidisciplinary Perspectives on Emerging Challenges, Opportunities, and Agenda for Research, Practice and Policy." *International Journal of Information Management* 57:101994. <https://doi.org/10.1016/j.ijinfomgt.2019.08.002>.
- Zoia, M. G., L. Barbieri, F. Cortelezzi, and G. Marseguerra. 2018. "The Determinants of Italian Firms' Technological Competencies and Capabilities." *Eurasian Business Review* 8(4):453–476. <https://doi.org/10.1007/s40821-018-0103-2>.

Appendix

Table A.1. Unconditional correlations (binary variables).

	R&D	Internal R&D	External R&D	ETC	AI 2022
R&D	1				
Internal R&D	0.867***	1			
External R&D	0.768***	0.557***	1		
ETC	0.168***	0.171***	0.175***	1	
AI 2022	0.206***	0.201***	0.189***	0.164***	1
Observations	936				

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.2. Conditional correlations (binary variables).

	R&D	Internal R&D	External R&D	ETC	AI 2022
R&D	1				
Internal R&D	0.819***	1			
External R&D	0.686***	0.396***	1		
ETC	0.0842**	0.0890**	0.0846**	1	
AI 2022	0.0636*	0.0655*	0.0466	0.105***	1
Observations	714				

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3. Industrial classification: high- and low-tech sectors.

Low-tech sector	High-tech sector
Meat products	Chemicals and pharmaceutical
Food and tobacco	Machinery and equipment
Beverage	Computer products, electronics and optical
Textiles and clothing	Electric materials and accessories
Leather, fur and footwear	Vehicles and accessories
Timber	Other transport equipment
Paper	
Printing	
Plastic and rubber products	
Non-metal mineral products	
Basic metal products	
Fabricated metal products	
Furniture	
Other manufacturing	

Note: Based on the OECD classification (see Hatzichronoglou 1997).