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R&D Cooperation: Direct and Indirect Effect and Complementary. An Oaxaca-Blinder Decomposition for a Developing Country

Carolina Pasciaroni 

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Abstract This paper examines the influence of R&D cooperation on the likelihood of obtaining technological innovations among manufacturing firms in Argentina. Using firm-level data from a national innovation survey, it distinguishes between the direct (output) and indirect (input) effects of cooperation by applying the Oaxaca-Blinder decomposition technique—rarely used in innovation studies. Indirect effects are assessed as complementarity or substitutability between R&D cooperation and a broad set of innovation activities, including both R&D and non-R&D efforts. The analysis also considers variations across technological sectors and types of cooperation partners (science and technology institutions vs. business partners). Results reveal a significant innovation performance gap in favour of cooperating firms. However, this gap is driven not by the direct or indirect effects of cooperation, but by firm characteristics—namely, internal R&D and the use of external information sources. Consequently, no evidence of complementarity or substitutability is found. These findings are consistent across sectors. The paper concludes with policy implications and future research directions.

Keywords R&D cooperation · Innovation performance · Direct/output effect and indirect/input effects · Complementary/substitutability · Oaxaca-Blinder decomposition, Argentina

JEL Classification Codes C20 · O31 · O39

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1 Introduction

Since the 1980s, several theoretical approaches have emphasised that innovation depends on knowledge that extends beyond the boundaries of individual firms (Lundvall 2007; Chesbrough et al. 2006; Tödtling et al. 2009; Arranz and de Arroyabe 2008). Within this framework, cooperation serves as a key mechanism for acquiring and transforming external knowledge, through joint projects, interactive knowledge exchange, shared practices, and capability building (Eurostat-OECD 2005; Tödtling et al. 2009; Audretsch et al. 2025)¹. In particular, joint R&D cooperation has become increasingly relevant in light of the growing complexity, risks, and costs involved in the innovation process (Hagedoorn et al. 2000; Belderbos et al. 2015; Becker and Dietz 2004, 2004; Audretsch et al. 2025).

From an empirical perspective, the impact of R&D cooperation on innovation performance at the firm level can be analysed by examining both the innovation output side (direct effects) and the innovation input side (indirect effects) (Aschhoff and Schmidt 2008; Becker and Dietz 2002, 2004; Barge-Gil and Modrego 2011). Following Becker and Dietz (2002, 2004), the direct/output effect refers to the increase in the probability of obtaining innovations from the implementation of additional capacities from outside, while, the indirect/input effects indicate the extension of firm technological capabilities of developing new products/process from adaptation of external resources within such arrangements.

These input-related effects, reflected in productivity gains from innovation activities, for instance greater R&D efficiency (Becker and Dietz 2002, 2004; Fritsch 2004; Barge-Gil and Modrego 2011), naturally lead to the literature on complementarity and substitutability between R&D cooperation, internal and external R&D, and non-R&D innovation activities such as acquisition of machinery and ICT, training, and industrial design and engineering (Hagedoorn and Wang 2012; Berchicci 2013; Serrano-Bedia et al. 2018; Zhang 2022; among others)². Based on the seminal contributions of Cassiman and Veugelers (2006), two innovation strategies are complementary if the implementation of one strategy increases the marginal returns of the alternative strategy³. This implies that the innovation performance derived from using one innovation knowledge source is higher if the complementary source is present at the same time and vice versa (Serrano-Bedia et al. 2018, p. 56).

¹ Following Audretsch et al. (2025), R&D collaboration involves the exchange of knowledge between two or more engaged partners through interactions, joint practices, and capability development. By contrast, knowledge spillovers refer to externally developed knowledge that is not entirely excludable and can be freely accessed by third parties as a positive externality. This distinction underscores the voluntary nature of knowledge exchange in R&D cooperation (Belderbos et al. 2004; Fritsch and Franke 2004).

² Following Zhang (2022), Santamaría et al. (2009), and Barge-Gil and Modrego (2011), innovation activities can be grouped into R&D and non-R&D. R&D activities focuses on generating new knowledge, while non-R&D activities—such as training, design, or advanced machinery—exploit existing knowledge. R&D activities may be conducted in-house (internal R&D), outsourced (external R&D), or undertaken with cooperation.

³ The empirical literature on complementarity and substitutability relationships uses varied terminology, including innovation activities (Radicic and Balavac 2019); innovation strategies (Cassiman and Veugelers 2002); innovation inputs (Radicic and Balavac 2019; Schmiedeberg 2008); sources of knowledge (Serrano-Bedia et al. 2018).

While several empirical studies have examined the direct impact of R&D cooperation on innovation performance (see Becker and Dietz 2002; Belderbos et al. 2004; Audretsch et al. 2023, 2025; among others), there remains limited understanding of its complementarity or substitutability relationships—particularly in environments characterised by low innovation dynamism, which constitutes the focus of this paper. Accordingly, the literature on complementarity/substitutability between innovation activities reveals empirical research gaps that the present study seeks to address, partly guided by the question: Which types of innovation activities should be combined with R&D cooperation to improve innovation performance in less dynamic innovation environments?

A first empirical research gap relates to the relatively limited exploration of complementarity/substitutability relationships involving R&D cooperation, as most existing studies focus on internal and external R&D (Radicic and Balavac 2019, p. 2). Second, the available empirical evidence is concentrated primarily in developed countries, with limited research examining developing economies, where innovation patterns differ markedly (see Radicic and Balavac 2019; Zhang 2022). For Argentina, **as in** other Latin American countries, non-R&D activities—such as the acquisition of machinery and ICT—play a significant role, while cooperation remains relatively scarce (Crespi and Dutrénit 2014; Dutrénit et al. 2019). Examining these scenarios is especially relevant given the mixed empirical evidence and context-specific nature of complementarity/substitutability relationships (Serrano-Bedia et al. 2018; Radicic and Balavac 2019; Wang et al. 2021).

Third, and building on this gap, most studies on complementarity/substitutability involving R&D cooperation focus primarily on its relationship with internal or external R&D, often overlooking other non-R&D innovation activities (Zhang 2022). Moreover, few studies have examined R&D cooperation in relation to a broad range of innovation activities (Serrano-Bedia et al. 2018). Fourth, limited attention has been devoted to whether complementarity/substitutability in R&D cooperation varies across productive sectors and types of cooperation partners (e.g. market-based vs science- and technology-based partners) (Park et al. 2024). This latter distinction is particularly relevant in Latin American countries, where national R&D efforts are predominantly carried out by universities and public science and technology institutions (Crespi and Dutrénit 2014; Dutrénit et al. 2019).

In order to address these empirical gaps, this paper examines both the direct and indirect effects of R&D cooperation among Argentine manufacturing firms. The indirect effects are explored through their complementarity or substitutability relationships with a diverse set of innovation activities, encompassing both R&D and non-R&D efforts. To this end, the study applies the Oaxaca–Blinder (OB) decomposition technique (Oaxaca 1973; Blinder 1973; Fortin et al. 2011) to a nationally representative firm-level dataset covering the period 2014–2016. The analysis further investigates whether the effects of R&D cooperation vary according to the type of cooperation partner and across technological sectors.

Beyond contributing to closing the identified empirical gaps, this paper also makes a methodological contribution by applying the Oaxaca–Blinder (OB) decomposition technique, which remains an uncommon approach in firm-level innovation research. The OB technique not only allows for the identification of the direct effects of R&D

cooperation and its indirect effects—capturing complementarity or substitutability relationships across a wide range of innovation activities—but also quantifies how much of the gap in innovation performance in favour of cooperating firms is explained by their own characteristics and how much by the effects of cooperation. In addition, the OB technique helps to overcome several limitations of traditional methods, including the supermodularity framework, which is commonly used to examine complementarity or substitutability relationships between innovation activities.

The paper is structured into five sections. The following section reviews the relevant literature. The third section describes the database, variables, and methodology—highlighting its advantages over conventional approaches—and provides an overview of the innovation profile of Argentina, within a broader Latin American perspective. The fourth section presents the empirical results. Finally, section five offers a synthesis and discussion of the findings, including limitations and directions for future research.

2 Literature Review

R&D cooperation provides a rich set of benefits to the the firm’s innovation process (Belderbos et al. 2015; Miotti and Sachwald 2003; Becker and Dietz 2002, 2004; Arranz and de Arroyabe 2008; Hagedoorn et al. 2000). Recently, Audretsch et al. (2025) synthesised the main motives for firms to engage in R&D cooperation, including the enhancement of absorptive capacity—a notion developed by Cohen and Levinthal (1990)—access to external expertise, cost reduction in development, and the acceleration of innovation in response to complex market and technological challenges. As noted in the Introduction, one analytical approach to address the influence that R&D cooperation has on firm innovation performance consists in discriminate between a direct/output effect and an indirect/input effects (Becker and Dietz 2004; Barge-Gil and Modrego 2011; Aschhoff and Schmidt 2008).

Concerning the direct impact of R&D cooperation, despite its recognised benefits, empirical evidence is inconclusive. Some firm-level studies for developed countries find a positive influence (Barge-Gil and Vivas-Augier 2019; Van Beers and Zand 2014; Robin and Schubert 2013; Becker and Dietz 2004; Belderbos et al. 2004; Aschhoff and Schmidt 2008; Audretsch et al. 2025, 2023) while others show limited or non-significant effects (Cassiman and Veugelers 2002; Fritsch and Franke 2004; Frenz and Ietto-Gillies 2009). For Latin America, there is empirical evidence in favour of the direct impact of R&D cooperation on the innovation performance of Brazilian firms (Santos et al. 2014; Jugend et al. 2018; Marin and Petralia 2018) and Argentinean firms (Arza and López 2011; Marin and Petralia 2018). Among other factors such as the type of partner involved, geographical proximity, and the firm’s sectoral affiliation, absorptive capacity is a key determinant in explaining the influence that R&D cooperation has on firms’ innovation performance (Kafouros et al. 2020; Kobarg et al. 2018; Badillo and Moreno 2015). Absorptive capacity refers to the firm’s ability to recognize the value of new external information, assimilate it and apply it to commercial ends (Cohen and Levinthal 1990). While R&D activities have traditionally been considered a key determinant of absorptive capacity, it is also

developed through processes of training and learning by doing (Cohen and Levinthal 1990; Vega-Jurado et al. 2008b) and no-R&D innovation activities (Hervas-Oliver et al. 2012; Zhang 2022).

For complementarity/substitutability relationships between innovation activities, the empirical findings are mixed and contingent on methodological approaches, country contexts, and innovation input-output measurements (Serrano-Bedia et al. 2018; Radicic and Balavac 2019; Zhang 2022). While most studies focus on the complementarity between internal and external R&D (e.g., Cassiman and Veugelers 2006; Schmiedeberg 2008; Grimpe and Kaiser 2010; Berchicci 2013; Arvanitis et al. 2015; Zhang and Qi 2023), only recently has attention turned to their interplay with R&D cooperation (Radicic and Balavac 2019), non-R&D inputs (Zhang 2022; Wang et al. 2021), and the combined effect of multiple innovation activities (Serrano-Bedia et al. 2018).

Focusing on R&D cooperation, several studies offer evidence in favour of complementarity with internal R&D (Cockburn and Henderson 1998; Becker and Dietz 2004; Schmiedeberg 2008; Gkypali et al. 2018; Ebersberger and Herstad 2012; Choi et al. 2012; Chen et al. 2016) and between R&D cooperation and external R&D (Gimenez-Fernandez and Sandulli 2017; Arvanitis et al. 2015; Grimpe and Kaiser 2010; Zhang and Qi 2023). Although not strictly related to cooperation, Carmona-Lavado et al. (2021), show complementarity between open innovation strategies—measured by the number of alliances and partner diversity—and firm-specific assets, including human capital, alliance coordination capabilities, and inter-organisational learning capabilities. Likewise, Arza et al. (2020) find that inter-sectoral spillovers enhance returns to internal R&D on the productivity of Argentine manufacturing firms. In contrast, other studies find no evidence to support the existence of a positive complementary effect between cooperation and internal R&D (Vega-Jurado et al. 2009; Arvanitis et al. 2015; Gesing et al. 2015); internal R&D and open innovation strategies (Laursen and Salter 2006); and between cooperation and external R&D (Ebersberger and Herstad 2012; Choi et al. 2012; Guisado González et al. 2014).

As previously noted, empirical literature examining the complementarity/substitutability relationships between cooperation and non-R&D activities remains scarce. Zhang (2022) investigates small and medium-sized firms that engage in non-R&D activities in China and finds evidence supporting the complementarity between cooperation—particularly with customers—and non-R&D activities, such as equipment and technology acquisition, training, and in-house development. Similarly, Wang et al. (2021), in their study on Germany, show that cooperation is positively associated with both the make strategy (internal R&D) and the buy strategy (acquisition of pre-embedded technology), with a stronger effect observed for the former.

A broad set of theoretical arguments has been proposed to explain the often contradictory evidence regarding the complementarity or substitutability between R&D cooperation and other innovation activities. Drawing on Serrano-Bedia et al. (2018), Radicic and Balavac (2019), and Zhang (2022), complementarity with internal R&D is primarily associated with absorptive capacity, the resource-based view, incoming knowledge spillovers, and economies of scope. In contrast, substitutability is linked

to switching costs, diseconomies of scope, the not-invented-here syndrome, transaction costs, opportunistic behaviour, and knowledge spillovers. Regarding external R&D, substitutability is again associated with switching costs and scope diseconomies, while complementarity may arise when collaborative experience improves firms' ability to select, manage, and monitor R&D outsourcing.

In terms of non-R&D innovation activities, training may complement R&D cooperation by enhancing a firm's absorptive capacity and improving its ability to engage effectively with external partners (Zhang 2022). R&D cooperation—especially with customers—may complement design activities, as effective design requires integrating external knowledge to ensure alignment with customer needs, product feasibility, and the firm's strategic positioning (Barge-Gil and Modrego 2011). Regarding the acquisition of machinery, ICTs, and other embodied technologies, cooperation can facilitate the assimilation of embedded knowledge, particularly through collaboration with suppliers (Arranz and de Arroyabe 2008; Van Beers and Zand 2014; Audretsch et al. 2023).

Given the context-specific and inconclusive nature of existing empirical findings—and in view of the limited number of studies examining complementarity/substitutability relationships in low-innovation countries such as Argentina—the following hypotheses explore the direct and indirect effects of R&D cooperation in such low-innovation settings:

H1: Firms that engage in R&D cooperation exhibit higher innovation performance compared to non-cooperating firms, due to the direct effects of cooperation.

H2: Firms that engage in R&D cooperation exhibit higher innovation performance compared to non-cooperating firms, as a result of indirect effects reflected in complementarities between R&D cooperation and internal R&D activities.

H3: Firms that engage in R&D cooperation exhibit higher innovation performance compared to non-cooperating firms, as a result of indirect effects reflected in complementarities between R&D cooperation and non-R&D innovation activities.

2.1 R&D Cooperation by Type of Partner and Firm Sectorial Affiliation

A key analytical focus of this study is to examine whether both the direct effect of R&D cooperation and its complementarity or substitutability relationships with other innovation activities vary according to the firm's sectorial affiliation and the type of cooperation partner. Following Arranz and de Arroyabe (2008), Van Beers and Zand (2014), and Audretsch et al. (2023), each cooperation partner type contributes specific knowledge and benefits to the firm's innovation process. Value chain partners—suppliers and customers—provide technological insights, market information, and feedback on product requirements, which help reduce risks and improve adoption. Horizontal cooperation with competitors enables cost and risk sharing in large-scale projects, while collaboration with universities and public research institutions grants access to scientific and technological knowledge that complements internal R&D through specialised expertise.

Once again, the empirical literature examining the complementarity/substitutability relationship between cooperation by partner type and specific innovation activities and specific innovation activities remains limited and inconclusive. Vega-Jurado et al. (2008a) and Gesing et al. (2015) report a substitution effect between internal R&D and cooperation with scientific partners, while Chen et al. (2016) finds no significant interaction effect. A similar pattern is observed for business partners: Gesing et al. (2015) and Chen et al. (2016) identify a substitution effect, whereas Vega-Jurado et al. (2008a) reports no significant joint effect. However, in a recent study on South Korea, Park et al. (2024) find complementary effects between firms' absorptive capacity and their interactions with science-based partners, whereas interactions with market-based partners had no significant effect on product innovation success.

The relevance of each cooperation partner is closely linked to the sectoral affiliation of the firm, as reflected in the innovation patterns described in sectoral taxonomies. According to the typology developed by Pavitt (1984) and subsequent contributions by Castellacci (2009) and Bogliacino and Pianta (2016), science-based industries—such as pharmaceuticals and electronics—rely on internal R&D, technology-embedded equipment, and university collaboration. Specialized-supplier industries, like machinery and equipment, combine R&D with tacit knowledge and customer interaction. Scale-intensive sectors, such as automotive and basic metals, rely on incremental innovation and economies of scale, while supplier-dominated industries, including food and textiles, depend on external inputs and limited internal R&D. For advanced economies, and following the OECD's sectoral classification based on internal R&D spending intensity, Hirsch-Kreinsen (2008), Santamaría et al. (2009), and Hansen and Winther (2011) note that in low- and medium-technology sectors, innovation relies on non-R&D activities—such as design, use of machinery and equipment, workforce qualifications, and training—to develop incremental innovations in collaboration with clients and suppliers.

There is still a lack of empirical evidence on how complementarity/substitutability between cooperation and innovation activities varies across sectors, even in developed countries. For the pharmaceutical industry, Hagedoorn and Wang (2012) find that internal R&D and external R&D, through either R&D alliances or R&D acquisitions, are complementary innovation activities at higher levels of in-house R&D investments, whereas at lower levels of in-house R&D efforts, internal and external R&D turn out to be substitutive strategic. For Italian manufacturing firms, Berchicci (2013) reports the opposite results: the substitution effect is larger for firms with greater R&D capacity. Similarly, Ebersberger and Herstad (2012) find that diversity in collaboration and internal R&D are complementary at low levels of R&D intensity. More recently, Wang et al. (2021) examined German firms in science-based and scale-intensive industries, providing evidence of the complementarity between cooperation, internal R&D, and the acquisition of capital with embodied technology.

The mutual influence between sectoral innovation patterns and national innovation systems suggests that taxonomies may require refinement to reflect substantial cross-country differences (Castellacci 2009). Thus, Latin American countries show distinctive features and dynamics of innovation captured through specific sectoral taxonomies (Marin and Petralia 2018; Katz and Stumpo 2001). One of the clearest

examples is natural resource-based industries, classified as low- and medium-tech industries in the OECD's taxonomy, are noted for their opportunities for innovation in Latin American countries (Pérez 2010; Dantas et al. 2013; Andersen et al. 2018; Marin and Petralia 2018). In addition, the traditional classifications designed for developed countries are based on internal R&D whereas, as a result of their comparative technological backwardness, Latin American firms tend to acquire knowledge incorporated in machinery, equipment, hardware, software, licences and technology transfer agreements. These activities allow the incorporation of knowledge available in the regional and global market.

Firm-level studies on complementarity/substitutability between R&D cooperation and other innovation strategies remain limited for Latin American countries. Marin and Petralia (2018) suggest that the higher effectiveness or rate of return from R&D observed in natural resource-based industries in Argentina and Brazil may be associated with the knowledge from scientific and educational institutions, suppliers and customers. For automotive and iron/steel industry in Argentina, current research reveals that significant complementarities exist between internal and external sources of knowledge (Álvarez et al. 2021).

Due to the limited and context-sensitive nature of existing evidence regarding how the effects of R&D cooperation vary by sector and partner type—particularly in less developed countries—the following hypotheses explore these dimensions in low-innovation settings:

H4: Firms that engage in R&D cooperation with business partners exhibit higher innovation performance compared to those cooperating with S&T partners. This advantage can be attributed to both a greater direct effect and a greater indirect impact, reflected in complementarities with other innovation activities.

H5: The effects of R&D cooperation on innovation performance—both direct and through complementarities—vary across industrial sectors.

3 Materials and Methods

3.1 Dataset

This study employs data from the National Survey of Employment Dynamics and Innovation 2014–2016 (ENDEI II), conducted jointly by Argentina's Ministry of Science, Technology and Innovation and the Ministry of Labour, Employment and Social Security. The survey was carried out on 3944 industrial firms with 10 or more employees during 2017 and 2018. The dataset contains information at firm-level on innovation and employment for the period 2014–2016. The ENDEI II questionnaire asks all firms, innovation-active firms and non-innovation-active ones, if they interacted with other agents to achieve certain goals associated with innovation activities such as R&D, technology transfer and industrial design and engineering, test and trials, human resources training, quality management and certification. In this questionnaire, interaction or cooperation is defined as a process in which part-

ners actively participate without the need to obtain an immediate commercial benefit from the interaction.

3.2 Variables

Based on the knowledge production function (Griliches 1979), the firm innovation performance constitutes the dependent variable. It is a binary variable referred to the introduction of product and/or process innovations. The vector of independent variables contains innovation activities variables, information sources variables as an alternative mechanism to access external knowledge by firms and, control variables (Table 1). Given the characteristics assumed by the innovation process in Latin American countries, it includes not only internal R&D and external R&D but also other innovation activities. Following Radicic and Balavac (2019), Serrano-Bedia et al. (2018), Cassiman and Veugelers (2006) and Belderbos et al. (2004), the innovation activities variables are defined as dummy variables (0/1) in order to avoid severe multicollinearity problems.

3.3 Method

The study applies the Oaxaca-Blinder decomposition technique (OB) (Oaxaca 1973; Blinder 1973; Fortin et al. 2011). The OB technique explains the gap in the means of an outcome variable between two groups of observations through the decomposition of such a gap into: (Eq. 1) an explained component attributable to differences in the magnitudes of observed characteristics or determinants of this outcome (X) and (Eq. 2) an unexplained component attributable to differences in the effects of these determinants or observed characteristic (differences in returns, coefficients β , effects or behavioural responses) (O'Donnell et al. 2008; Jann 2008). This second component also includes differences in the return of unobservable characteristics (Fortin et al. 2011) and can be interpreted as a treatment effect or a measure of discrimination (Fortin et al. 2011; Jann 2008).

The decomposition into the two components mentioned is called twofold decomposition. In the threefold decomposition, three components are identified: Eq. 1 differences in endowments or observed characteristics (E); Eq. 2 differences in the coefficients (including the constant) (C) and Eq. 3 differences in the endowments and coefficients simultaneously (interaction component EC). The unexplained component is made up of C component (coefficients effect) and EC component (interaction component). Based on Jann (2008), given two groups, A and B , for a liner model $Y_l = X_l' \beta_l + \varepsilon_l$, $E(\varepsilon_l) = 0 \mid l \in (A, B)$, where X is a vector containing the predictors and a constant, β contains the slope parameters and the intercept, and ε is the error, the mean outcome difference can be expressed as:

$$R = E(Y_A) - E(Y_B) = E(X_A)' \beta_A - E(X_B)' \beta_B \quad (1)$$

Table 1 Variables. Definition and descriptive statistics. Full sample. (Source: Own elaboration based on ENDEI II survey)

Variable	Definition	Obs	Mean	Std. Dev
Dependent variable	Inno.tech	3905	0.7032	0.4569
Control variables	Size	3898	3.6486	1.0860
	Foreign	3944	0.0842	0.2777
	Export	3944	0.3200	0.4665
	Age	3944	0.4490	0.4975
	Tech. intensity	3944	0.2003	0.4003
	Inputs or innovation activities	R&D activities	3944	0.4087
	External R&D	3944	0.1648	0.3711
	Non-R&D activities	3944	0.4622	0.4986
	Tech. transfer	3944	0.1270	0.3330
	ME & ICT	3944	0.6197	0.4855
	Training	3944	0.3820	0.4859
Other innovation variables	Frequency	3944	0.260	0.439
	Financing	3944	0.3286	0.4698
	Market inf. sources	3944	0.5020	0.5001
	S&T inf. sources	3944	0.1349	0.3416
	Available inf	3944	0.4726	0.4993
Variable that defines groups to be compared	R&D_coop	3926	0.1956	0.3967

In some variables, the number of observations less than the full sample is due to the non-inclusion of observations with a don't know/don't answer response

For a linear model, the threefold decomposition formulated from the viewpoint of group B:

$$R = \underbrace{\frac{\{E(X_A) - E(X_B)\}' \beta_B}{E(\text{endowments})}}_{I(\text{interaction})} + \underbrace{\frac{+E(X_B)'(\beta_A - \beta_B)}{C(\text{coefficients})}}_{C(\text{coefficients})} \quad (2)$$

For a linear model, the twofold decomposition formulated from the viewpoint of group B:

$$R = \underbrace{\frac{\{E(X_A) - E(X_B)\}' \beta_B}{Q(\text{explained})}}_{Q(\text{explained})} + \underbrace{\frac{+E(X_A)'(\beta_A - \beta_B)}{U(\text{unexplained})}}_{U(\text{unexplained})} \quad (3)$$

Starting from a nonlinear specification and following Fortin et al. (2011, p. 51), if Y is a dichotomous outcome variable ($Y = 0; 1$) and $Y_G^* = X\beta_g + v_g$ is a latent variable which is linear in X , the conditional expectation of Y is typically modelled as a non-linear function $E[Y_g|X; \beta_g] = G(X\beta_g)$ where $G(\cdot)$ is the cumulative distribution function (CDF) of v_g , X is the vector of covariates $X_i = [X_{i1} \dots; X_{iK}]$ and g represents the groups or subsamples A and B. Under various assumptions regarding the functional form $G(\cdot)$ and/or the distribution of the error terms v_g , the models are estimated by maximum likelihood. The mean gap between group B (D_B indicator variable of group B membership) and group A (D_A indicator variable of group A membership), is then decomposed as follows if group A is the reference group:

$$\begin{aligned} \Delta_0^\mu &= E(Y_B|D_B = 1) - E(Y_A|D_A = 1) \\ &= \underbrace{E[G(X; \beta_B)|D_B = 1] - E[G(X; \beta_A)|D_A = 1]}_{\Delta_x^\mu(\text{explained})} \\ &= \underbrace{E[G(X; \beta_B)|D_B = 1] - E[G(X; \beta_A)|D_A = 1]}_{\Delta_s^\mu(\text{unexplained})} + \underbrace{E[G(X; \beta_B)|D_B = 1] - E[G(X; \beta_A)|D_B = 1]}_{\Delta_s^\mu(\text{unexplained})} \end{aligned} \quad (4)$$

Δ_0^μ = overall difference in average outcomes between group B and A

Δ_x^μ = component that attributes differences in the mean outcome variable to differences in characteristics

Δ_s^μ = component that attributes differences in the mean outcome variable to differences in coefficients.

For the purpose of this paper, $G(\cdot)$ is a logistic cumulative distribution function for a binary variable that indicates if the firm has introduced product and/or process innovations. Thus, the OB technique is based on the estimation of a logistic model by maximum likelihood for each of the two firm groups (A and B). The proposed study compares the innovation performance between:

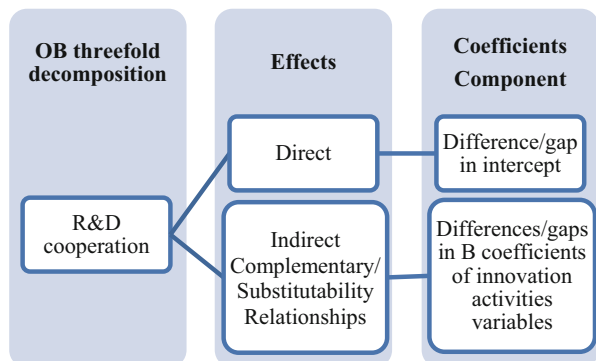
1. firms that cooperate for R&D (Group A) and firms that do not cooperate for R&D (Group B);
2. firms that cooperate for R&D with S&T partners (Group A) and those that cooperate for R&D with business partners (Group B).

These two comparisons are made on the full sample and the firms divided according to their affiliation to high and medium-high technology (HMHT) and low and medium-low technology (LMLT) manufacturing sectors. This paper uses the CIECTI (2020) classification based on the intensity of domestic innovation spending, including R&D (see Table 6 in the Appendix).

Figure 1 illustrates how the direct and indirect effects of R&D cooperation—translated into complementarity or substitutability relationships with other innovation activities—can be identified through the threefold detailed OB decomposition. In this framework, for k innovation activities variables, the coefficient component (C) captures the portion of the innovation performance gap attributable to differences in estimated coefficients β_k , holding input levels constant \bar{X}_K (see Eq. 3). While differences in coefficients—returns to innovation activities—reflect indirect effects of R&D cooperation, the intercept gap captures its direct effect, as it reveals the influence of group membership (Jann 2008; Fortin et al. 2011). Besides, the intercept gap may signal the presence of unobserved firm-level effects or omitted variables (Fortin et al., p. 91).

Since the results of the OB decomposition change according to the choice of the reference group ('the index problem'), variations of OB decomposition using a different reference vector of coefficient β^* are estimated in order to provide a range of decomposition values (Jann 2008). Thus, the decomposition is formulated from the perspective of Group A, Group B and the reference coefficients proposed by Cotton (1988), Reimers (1983) and Neumark (1988). The detailed decompositions are estimated only for $\beta^* = \beta_A$ and $\beta^* = \beta_B$. Given that in non-linear decomposition the results depend on the order of the variables X (path-dependence), the OB decompositions are estimated following the method proposed by Yun (2004).

Fig. 1 R&D cooperation and innovation performance in OB decomposition. (Source: Own elaboration based on Jann 2008)



3.4 The Oaxaca–Blinder Decomposition: Advantages Over Conventional Empirical Approaches

The OB methodology is seldom used in firm-level innovation research, yet it offers valuable insights into the drivers of disparities in innovation outcomes between groups of firms—such as cooperating and non-cooperating ones. It decomposes the overall gap into a component attributable to differences in endowments (observable characteristics) and another stemming from differences in the returns to those characteristics (estimated coefficients) (O'Donnell et al. 2007; Jann 2008), thus providing a structured interpretation of innovation gaps. The approach is flexible across functional forms and accommodates robust estimation techniques, including instrumental variables (Fortin et al. 2011)⁴.

Moreover, this paper employs the OB methodology, given its advantages over standard approaches to examining complementarity/substitutability relationships. According to reviews by Wang et al. (2021), Radicic and Balavac (2019), Serrano-Bedia et al. (2018), and Schmiedeberg (2008), the literature identifies two main approaches to assessing complementarity or substitutability between innovation activities: the adoption or indirect approach, and the production or direct approach. The indirect approach, grounded in revealed preferences, examines the correlation between innovation activities, assuming that complementary activities are adopted jointly (e.g. Schmiedeberg, 2008; Serrano-Bedia et al. 2018). However, it captures co-occurrence rather than causal effects on innovation outcomes (Mohnen and Röller 2005).

The production approach tests for complementarity/substitutability by including interaction in econometric models (e.g. Cassiman and Veugelers 2006). However, this method faces several limitations, including multicollinearity (Serrano-Bedia et al. 2018; Zhang 2022) and interpretation challenges in nonlinear model, where the interaction effect does not equal the marginal effect of the interaction term, may have the opposite sign, and can vary in sign across observations (Ai and Norton 2003; Serrano-Bedia et al. 2018). As suggested by Serrano-Bedia et al. (2018), these issues can be mitigated by modelling innovation activities as discrete-choice variables and applying the supermodularity framework.

Briefly, the supermodularity framework tests for complementarity/substitutability based on the estimated coefficients of mutually exclusive innovation combinations, under a set of restrictions that must be satisfied to confirm complementarity (e.g. Cassiman and Veugelers 2006; Schmiedeberg 2008; Barge-Gil and López 2013; Arvanitis et al. 2015; Serrano-Bedia et al. 2018). Nevertheless, this method entails drawbacks when analysing multiple innovation activities, including high multicollinearity (Morero and Ortiz 2017), few observations per exclusive category (Morero and Ortiz 2017), and difficulties in interpreting numerous interaction terms

⁴ Following Słoczyński (2020), who draws on Fortin et al. (2011), endogeneity may arise from unobserved covariates with different correlation patterns, though this does not compromise identification of the aggregate decomposition unless the conditional independence assumption is violated. In light of the results concerning the intercept gap in the coefficient component (C) of the detailed threefold Oaxaca–Blinder decomposition (see next section), this paper does not undertake an explicit treatment of endogeneity. Nonetheless, this remains a relevant avenue for future research.

(Serrano-Bedia et al. 2018). Additionally, the procedure becomes excessively tedious, as the number of supermodularity constraints grows rapidly with the number of innovation types—specifically,

$$2^{(k-2)} \sum_{i=1}^{k-1} i,$$

where k denotes the number of activities (Zhang 2022, p. 5).

To address these limitations, the analysis of the coefficient component (C) in the detailed threefold Oaxaca–Blinder decomposition offers an alternative for test the existence of direct effect and complementarity/substitutability relationships between one innovation activity and several others, as well as for evaluating the magnitude of these relationships. Besides, the coefficient component (C) not only reflects differences in coefficients between groups but also captures scale effects, as its actual impact on each β_k the outcome gap depends on the distribution of explanatory variable X_k within each group. It should be emphasised that it is common practice in this field of research to use binary indicators for innovation activities to avoid multicollinearity, consequently overlooking continuous variables that would allow capturing not only firms' engagement but also scale effects (Radicic and Balavac 2019).

3.5 Context

This research focuses on Argentina, an upper-middle-income country ranked 76th out of 133 economies in the Global Innovation Index (GII) 2024, underperforming relative to its level of development (WIPO 2024). Within its income group, it holds 21st position among 34 countries, and in Latin America and the Caribbean, it ranks 8th, behind Chile (50th), Brazil (54th), and Mexico (58th). The GII 2024 report highlights structural weaknesses in Argentina's innovation system, including a limited number of leading R&D firms, low capital formation, and modest labour productivity. Argentina also shares characteristics with other countries in the region, such as low R&D expenditure as a percentage of GDP and a predominantly public-sector-driven R&D funding structure, with business-sector participation falling below the OECD average.⁵

At the firm-level, Latin American companies concentrate their innovation efforts on the acquisition of machinery and equipment; cooperate to a lesser extent than firms from developed countries (Crespi and Dutrénit 2014; UNESCO 2017; Arocena and Sutz 2020) and these interactions T are not centred on R&D projects but on the provision of technological and business services and human resource training (Arza and López 2008; Llisterri and Pietrobelli 2016).

Thus, national innovation systems in Latin America and the Caribbean have been characterised historically by limited scale and weak linkages among key actors (Crespi and Dutrénit 2014; Albornoz 2009). Persistent challenges include low

⁵ Country profiles are available on STIP Compass, a portal developed by the European Commission and the OECD: <https://stip.oecd.org>. For Argentina, see EC/OECD (2024).

absorptive capacity, fragmented collaboration networks, significant distortions in incentive structures, and low levels of patenting (op. cit.). According to Crespi and Dutrénit (2014) and Arocena and Sutz (2020), since the 2000s, science, technology and innovation (STI) (STI) policies in Latin America have transitioned from a marginal role—initially as appendages to industrial or market policies—to a systemic approach aligned with international standards. This shift acknowledges that isolated support to firms is insufficient to address coordination failures and externalities, prompting stronger linkages between academia and industry. Consequently, countries like Argentina, Brazil, Chile, and Colombia have implemented initiatives promoting collaborative research and innovation, fostering partnerships between public research organisations and private enterprises⁶.

4 Empirical Results

4.1 Innovation Gap Between Cooperating and Non-Cooperating Firms: a Premise for the Oaxaca-Blinder Decomposition

Before displaying the results of the Oaxaca-Blinder (OB) technique, Pearson's chi-square test (Table 2) reports statistically significant differences in the share of firms that achieved technological innovations between cooperating (Group A) and non-cooperating firms (Group B), supporting the application of the OB method. The observed advantage among cooperating firms is consistent with Cramér's V coefficient, which indicates a positive and moderate association between cooperation and innovation, with a slightly wider gap in LMLT sectors. Between cooperating and non-cooperating firms, the OB technique compares their endowments in X 's (means and proportions) reported in Table 7 in the Appendix, and their estimated β 's derived from logit model estimations shown in Table 8 in the Appendix.

Table 2 also shows the proportion of innovative firms that engage in R&D cooperation with business partners exclusively and firms that engage in R&D cooperation with S&T partners exclusively. Pearson's chi-square test reports statistically significant differences in the proportion of innovative firms between these two types of cooperation only for the full sample. Nonetheless, Cramér's V indicates a low association between innovation performance and cooperation by partner type. In line with this weak association, the application of the OB technique does not show significant differences in the predicted probability of introducing technological innovations between these groups of firms⁷. Since Pearson's chi-square test does not report statistically significant results for HMHT and LMLT, the OB decomposition is not performed by partner type. To summarise, the evidence presented in Table 2 regarding partner type does not support the validation of hypothesis H4 proposed in this paper.

⁶ From country profiles are available on STIP Compass, a portal developed by the European Commission and the OECD: <https://stip.oecd.org>.

⁷ Estimates available upon request.

Table 2 Innovative performance by cooperating vs. non-cooperating firms and by cooperation partner type. (Source: Own elaboration based on ENDEI II survey)

Difference in the percentage of innovative firms between Group A and Group B		GROUP A firms		GROUP B firms		Observed gap A-B	GROUP A cooperating firms	GROUP B cooperating firms	Observed gap A-B
	Cooperating	Non-cooperating	Cooperating	Non-cooperating	Observed gap A-B	Observed gap A-B	S&T partners	Business partners	Observed gap A-B
<i>Full sample</i>	94.40% (n = 768)	64.48% (n = 3128)	29.92 pp	91.21% (n = 273)	95.78% (n = 332)	-4.57 pp			
Pearson chi2 (1)	264.7684***			5.3253***					
Cramér's V	0.2607			-0.0938					
<i>HMHT sectors</i>	96.11% (n = 180)	72.76% (n = 602)	23.35 pp	94.12% (n = 68)	95.95% (n = 71)	-1.83 pp			
Pearson chi2 (1)	44.2331***			0.2528					
Cramér's V	0.2378			-0.0422					
<i>LMLT sectors</i>	93.88% (n = 588)	62.51% (n = 2526)	31.37 pp	90.24% (n = 205)	95.74% (n = 247)	-5.5 pp			
Pearson chi2 (1)	217.2483***			5.5164					
Cramér's V	0.2641			-0.1092					

Full sample and industrial sector subsamples

Values in parentheses refer to the number of observations comprising each group

pp percentage points

* p-value ≤ 0.10 **p-value ≤ 0.05 ***p-value ≤ 0.01

4.2 Overall OB Decomposition for Innovation Gap Without Partner-Type Distinction

Moving to the OB technique results, Table 3 shows the predicted probability of obtaining technological innovations for cooperating firms (Group A) and non-cooperating firms (Group B). With figures similar to those from the descriptive statistics (Table 2), Table 3 shows that the predicted probability of obtaining technological innovations for the full sample is 0.943 for Group A and 0.6381 for Group B, yielding a difference of 30.52 percentage points. Once again, the largest gap in predicted probabilities is observed in the LMLT sector.

Table 3 also exhibits OB estimates using different β^* to enhance the robustness of the findings, given that the OB technique is sensitive to the choice of the reference coefficient β^* used to calculate the components of the OB twofold decomposition (explained and unexplained) as well as the threefold decomposition (endowments, coefficients, and interaction effects).

In all types of twofold and threefold estimations shown in Table 3, except for the OB decompositions from the perspective of $\beta^* = \beta_A$ for HMHT sectors, the results show that differences in endowments (X 's) across groups are greater in magnitude than variations in coefficients (β 's). Thus, the similarities across the different OB estimations defined by β^* not only enhance the robustness of the analysis but also provide an insight into the primary drivers of the innovation gap that is, the endowments component. The next detailed OB decomposition analysis will determine which coefficient differences contribute to the gap, revealing complementarity/substitutability relationships between R&D cooperation and other innovation activities.

4.2.1 Detailed Threefold OB Decomposition: Endowments and Coefficients

Table 4 displays the detailed decomposition for threefold OB estimates from the perspective of $\beta^* = \beta_A$ and $\beta^* = \beta_B$. In $\beta^* = \beta_A$, it is assumed that the cooperating firms constitute the reference group and the non-cooperating firms show lower innovation performance (similar to the notion of negative discrimination). In $\beta^* = \beta_B$, it is assumed that the non-cooperating firms constitute the reference group and the cooperating firms show higher performance compared to this reference group (similar to positive discrimination).

For the contribution of each X_k to the endowment component (E), the gaps in the variables internal R&D, use of information market sources and, use of available information sources are statistically significant and show a positive sign in all the estimated OB decompositions for $\beta^* = \beta_B$ (Table 4). This indicates that if the group of firms that does not cooperate increases the endowment or percentage of firms that carry out internal R&D or use external information sources, the gap in innovation performance would decrease. In addition, according to the magnitude of the point estimates, the greatest contributions to the E component are observed in the mentioned variables. Table 7 in the Appendix shows the observed mean of each independent variable for each group of firms. The contribution of the remaining independent variables to the E component depends on the type of OB estimate and the

Table 3 OB decomposition by reference coefficient for the full sample and industrial sector subsamples. (Source: Own elaboration based on ENDEI II survey)

Dependent variable: Imo.tech	Full sample		HMHT sectors		LMLT sectors	
	Coef	S.E.	Coef	S.E.	Coef	S.E.
Prediction group A	0.9433***	0.0073	0.9576***	0.0148	0.9379***	0.0084
Prediction group B	0.6381***	0.0076	0.7245***	0.0153	0.6175***	0.0087
Difference	0.3052***	0.0105	0.2330***	0.0213	0.3204***	0.0121
$\beta^* = \beta_B$	0.2837***	0.0076	0.2065***	0.0146	0.2984***	0.0090***
	0.0215**	0.0083	0.0268	0.0170	0.0220**	0.0097**
$\beta^* = \beta_A$	0.2041***	0.0278	0.0916*	0.0494	0.2338***	0.0322
Neumark	0.1011**	0.0326	0.1414**	0.0581	0.0866**	0.0375
	0.2817***	0.0074	0.2039***	0.0146	0.2965***	0.0087
Reimers	0.0236**	0.0080	0.0291*	0.0163	0.0239**	0.0093
	0.2453***	0.0142	0.1495***	0.0309	0.2660***	0.0168
	0.0599***	0.0185	0.0835**	0.0383	0.0544**	0.0216
Cotton	0.2727***	0.0080	0.1911***	0.0158	0.2888***	0.0094
	0.0326**	0.0105	0.0419**	0.0207	0.0317**	0.0123
Threefold $\beta^* = \beta_B$	0.2783***	0.0076	0.2063***	0.0146	0.2984***	0.0090
	0.0976**	0.0323	0.1414**	0.0581	0.0866**	0.0375
	-0.0769**	0.0275	-0.1146**	0.0500	-0.0646**	0.0322
Threefold $\beta^* = \beta_A$	0.2041***	0.0278	0.0916*	0.0494	0.2338***	0.0322
	0.0215**	0.0083	0.0268	0.0170	0.0220**	0.0097
	0.0796**	0.0278	0.1146**	0.0500	0.0646**	0.0322

Logistic model

Robust standard errors

* p -value ≤ 0.10 ** p -value ≤ 0.05 *** p -value ≤ 0.01

Table 4 Threefold detailed OB decomposition for $\beta^* = \beta_A$ and $\beta^* = \beta_B$ (Source: Own elaboration based on ENDEI II survey)

Dependent variable:	Full sample			HMHT sectors			LMLT sectors		
	$\beta^* = \beta_B$	$\beta^* = \beta_A$	S.E.	$\beta^* = \beta_B$	$\beta^* = \beta_A$	S.E.	$\beta^* = \beta_B$	$\beta^* = \beta_A$	S.E.
Inno.tech	Coef	Coef	S.E.	Coef	Coef	S.E.	Coef	Coef	S.E.
Endowments									
Size	-0.0004	-0.0026	0.0101	-0.0004	0.0027	0.0068	-0.0004	0.0041	0.0126
Foreign	-0.0009	-0.0016	0.0022	-0.0023	0.0052	(omitted)	-0.0019	0.0016	0.0034
Export	0.0058	0.0135	0.0104	0.0091	0.0061	0.0135	0.0045	0.0042	0.0124
Frequency	0.0092*	0.0114	0.0136	0.0182*	0.0096	0.0184	0.0056	0.0063	0.0164
Age	0.0006	0.0027	0.0044	-0.0006	0.0012	0.0019	0.0012	0.0016	0.0057
Internal R&D	0.0687***	0.0374**	0.0191	0.0774***	0.0179	0.0323	0.0628***	0.0109	0.0355*
External R&D	0.0164*	-0.0033	0.0138	0.0156	0.0235	0.0220	0.0142	0.0107	0.0157
Design & Eng	0.0226***	-0.0105	0.0224	0.0135	0.0110	0.0340	0.0239***	0.0073	0.0259
Tech. transfer	0.0154***	0.0054	0.0121	0.0053	0.0099	0.0125	0.0189***	0.0068	0.0176
ME & ICT	0.0297***	0.0409***	0.0156	0.0122	0.0086	0.0240	0.0352***	0.0059	0.0488***
Training	0.0142**	0.0241	0.0182	0.0120	0.0105	0.0133	0.0139*	0.0079	0.0227
Financing	0.0078**	0.0055	0.0107	0.0084	0.0074	0.0117	0.0071	0.0044	0.0121
Market inf.	0.0578***	0.0405***	0.0131	0.0360***	0.0095	0.0221	0.0637***	0.0074	0.0370***
Sources									
S&T inf.	-0.0067	0.0000	0.0143	-0.0312	0.0235	0.0240	0.0027	0.0151	0.0167
Sources									
Available inf	0.0442***	0.0397***	0.0143	0.0330**	0.0138	0.0218	0.0471***	0.0081	0.0557***
Tech. intensity	-0.0006	0.0011	0.0025	-	-	-	-	-	-
Size	-0.0259	-0.0354	0.2185	0.5710	0.4432	0.9144	-0.0680	0.1009	-0.0262
									0.0418

Table 4 (Continued)

Dependent variable:	Full sample			HMHT sectors			LMLT sectors					
	$\beta^* = \beta_B$	Coef	S.E.	$\beta^* = \beta_A$	Coef	S.E.	$\beta^* = \beta_B$	Coef	S.E.	$\beta^* = \beta_A$	Coef	S.E.
Inno.tech												
Endowments												
Foreign	-0.0027	0.0078	0.0212	-0.0048	0.0212	0.0149	(omitted)	-0.0022	0.0057	-0.0013	0.0034	0.0034
Export	0.0161	0.0212	0.1252	0.0359	0.1252	0.1313	0.1433	0.0219	0.0169	0.0142	0.0136	0.0136
Frequency	0.0040	0.0184	0.0561	0.0111	0.0561	0.1450	0.1075	0.0107	0.0139	0.0088	0.0118	0.0118
Age	-0.0162	0.0350	0.0638	-0.0150	0.0638	0.0923	0.0842	-0.0211	0.0308	-0.0053	0.0087	0.0087
Internal R&D	-0.0290	0.0279	0.3079	-0.0830	0.3079	0.2288	0.4097	-0.0131	0.0189	-0.0113	0.0184	0.0184
External R&D	-0.0126	0.0117	0.1853	-0.0510	0.1853	0.0669	0.0409	-0.0091	0.0089	-0.0107	0.0126	0.0126
Design & Eng	-0.0547	0.0372	0.4058	-0.1268	0.4058	0.1650	0.2362	-0.0397	0.0273	-0.0268	0.0210	0.0210
Tech. transfer	-0.0081	0.0135	0.1042	-0.0262	0.1042	0.0529	0.2290	0.0022	0.0132	0.0020	0.0115	0.0115
ME & ICT	0.0460	0.0465	0.2810	0.0836	0.2810	0.2166	0.0942	0.0422	0.0349	0.0218	0.0214	0.0214
Training	0.0172	0.0281	0.1549	0.0432	0.1549	0.0781	0.0750	0.0129	0.0231	0.0094	0.0185	0.0185
Financing	-0.0035	0.0263	0.0567	-0.0071	0.0567	0.0834	0.0858	0.0002	0.0206	0.0001	0.0120	0.0120
Market inf.	-0.0255	0.0343	0.2107	-0.0530	0.2107	0.0680	0.1628	-0.0244	0.0296	-0.0147	0.0226	0.0226
Sources												
S&T inf.	0.0023	0.0071	0.0624	0.0149	0.0624	0.0413	0.3076	-0.0015	0.0053	-0.0029	0.0106	0.0106
Sources												
Available inf	0.0003	0.0284	0.0640	0.0006	0.0640	0.2539	0.3966	0.0202	0.0185	0.0132	0.0120	0.0120
Tech. intensity	0.0121	0.0186	0.0596	0.0177	0.0596	0.5219	0.1511	0.1553	0.1384	0.0514	0.0601	0.0601
cons	0.1812	0.1666	0.2168	0.2168	0.2168	-	-	-	-	-	-	-

Full sample and industrial sector subsamples
 The detailed decomposition for the interaction component is not included in Table 4 since no significant individual contributions are identified for any of the variables included in the model

Robust standard errors

* p -value ≤ 0.10 ** p -value ≤ 0.05 *** p -value ≤ 0.01

set of firms. It is highlighted that, among firms engaging in R&D cooperation within LMLT sectors, the higher endowments in training, industrial design and engineering, acquisition of machinery, equipment, and ICT, and investment in technology transfer help explain the gap in innovation performance in OB decompositions for $\beta^* = \beta_B$.

The contribution of each β_K to the coefficient component (C) for innovation activity variables—internal R&D, external R&D, design & engineering, technology transfer, ME & ICT, training—assumes special attention given the objectives set out in this paper about complementary/substitutability relationships of R&D cooperation. It is essential to highlight that, following Jann (2008), for a linear model, the threefold OB decomposition, formulated from the viewpoint of Group B, expresses the coefficient component as $C = E(X_B)'(\beta_A - \beta_B)$. Thus, the OB decomposition weights differences in β_K using the mean values of the explanatory variables X_K providing a more precise estimation of their contribution to the innovation gap.

When examining the magnitudes reported in Table 4, the differences in the β_K coefficients associated with innovation activities contribute only marginally to the overall innovation gap. For instance, in the case of internal R&D activities for the full sample, the contribution amounts to -2.90 percentage points (second column of Table 4), representing 9.5% of the estimated gap, which stands at 30.52 percentage points (Table 3). Moreover, none of the gaps in the β_K coefficients associated with innovation activities are statistically significant, therefore, no complementarity or substitutability relationships are identified between R&D cooperation and the innovation activities analysed.

As a robustness check of the findings, the analysis of complementarity/substitutability relationships in R&D cooperation based on the OB decomposition can be combined with a Wald test for coefficient equality, derived from group-specific logistic estimations (see Table 8 in the Appendix)⁸. The Wald test, reported in Table 9 in the Appendix, reveals that none of the differences in β are statistically significant. This result provides additional evidence suggesting that no complementarity or substitutability relationships exist between R&D cooperation and the innovation activities considered. Consequently, the evidence presented in Table 4 does not support the validation of hypotheses H1–H3 and H5 proposed in this paper.

Finally, the intercept gap is not statistically significant across all detailed OB decompositions (Table 4), suggesting that there is no direct effect of R&D cooperation *per se*. Moreover, this result indicates the absence of unobserved firm-level factors or omitted variables, which would otherwise be captured by this component. Nevertheless, these effects cannot be entirely ruled out, as the coefficient and the unexplained component are statistically significant in most OB estimations (Table 3), even though the individual contributions of each variable are not (Table 4). This implies that the unexplained gap is not driven by any specific variable—a common finding in OB studies (e.g., Kieny et al. 2021; Tabrizi et al. 2025)—suggesting potential unobserved effects (Fortin et al. 2011; Jann 2008), and highlights a limitation

⁸ The OB decomposition extends beyond a coefficient equality test by weighting differences in each β_K coefficients using the mean values of the explanatory variables X_K providing a more precise estimation of their differential impacts on the innovation performance.

Table 5 R&D cooperation. Summary of results for full sample and industrial sector subsamples. (Source: Own elaboration)

Hypothesis	Support	Summary of Findings
H1	Not supported	No direct effects of R&D cooperation are identified for the full sample, nor for LMLT and HMHT sectors
H2	Not supported	No indirect effects or complementarity relationships are identified between R&D cooperation and internal/external R&D for the full sample, LMLT, and HMHT sectors
H3	Not supported	No indirect effects or complementarity relationships are identified between R&D cooperation and non-R&D innovation activities for the full sample, LMLT, and HMHT sectors
H4	Not supported	No differences in innovation performance are identified between firms cooperating with business partners and those cooperating with S&T partners
H5	Not supported	No sectoral differences are identified in the effects of R&D cooperation on innovation performance

of the method: it reveals unexplained differences but does not identify their precise sources.

Beyond the considerations regarding the statistical significance of each β 's contribution to the coefficient component—including the intercept (Table 4)—the limited magnitude of both the aggregated coefficient component (in the threefold OB decomposition) and the unexplained component (in the twofold OB decomposition) in explaining the higher innovation performance of cooperating firms (Table 3) provides further indication of the absence of a substantial direct or indirect effect of R&D cooperation. Table 5 presents a synthesis of the results on the direct effect of R&D cooperation and on complementarity/substitutability relationships—indirect effects—between R&D cooperation and other innovation activities.

5 Discussion

5.1 Synthesis and Discussion

Owing to its widely recognised benefits for innovation performance, this paper examines R&D cooperation in technologically lagging environments, focusing on both its direct and indirect effects on innovation outcomes at the firm-level. Since indirect effects are conceptually linked to the seminal contributions of Cassiman and Veugelers (2006) on complementarity/substitutability relationships between innovation activities, the analysis explores whether, in low-innovation contexts, the simultaneous occurrence of R&D cooperation and other innovation activities yields a joint effect on performance, either through complementarity or substitutability.

The Argentine manufacturing sector offers a suitable setting to examine the effects of R&D cooperation, due to two interrelated factors: the mixed and context-dependent nature of complementarity/substitutability relationships, and the predominance of empirical studies focused on developed economies. As outlined previously, Argentina—like other Latin American countries—exhibits innovation patterns that differ markedly from those of developed economies, including a historically low

propensity to engage in cooperative strategies—despite their sustained promotion in academic and policy discourse (Crespi and Dutrénit 2014; Dutrénit et al. 2019; Arocena and Sutz 2020). These contextual specificities underscore the importance of assessing how R&D cooperation interacts with other innovation strategies in such environments.

Briefly, the empirical findings indicate that industrial firms in Argentina engaging in R&D cooperation are more likely to achieve technological innovation than non-cooperating firms. This pattern holds across both low- and medium-low-technology (LMLT) and high- and medium-high-technology (HMHT) sectors, with a more pronounced gap in favour of cooperating firms in LMLT sectors. However, according to the Oaxaca–Blinder decomposition estimates, this gap is primarily attributable to differences in observable characteristics between firm groups, rather than to differential returns to the explanatory variables. Among these characteristics, cooperating firms exhibit greater endowments in areas such as internal R&D and the use of generally available and market information sources. In the case of LMLT sectors, the innovation gap is also explained by a higher proportion of cooperating firms engaging in training, industrial design and engineering, and the acquisition of machinery and equipment—non-R&D innovation activities that are particularly relevant in LMLT sectors (Santamaría et al. 2009; Zhang 2022). Notably, these innovation activities are also positively associated with the likelihood of engaging in R&D cooperation in Latin American countries (ECLAC 2011; de Moraes Silva et al. 2018; Arza and López 2011).

In addition, the coefficient component (C) in the detailed threefold Oaxaca–Blinder decompositions—for the full sample as well as for the LMLT and HMHT sectors—indicates that neither the differences in the innovation input coefficients nor the gap in the intercept are statistically significant. Accordingly, the results provide no evidence of complementarity or substitutability relationships between R&D cooperation and the innovation activities included in the model, nor of a direct effect of cooperation per se. These findings are consistent with previous studies reporting a lack of synergistic effects between internal R&D, external R&D, and cooperation. This includes evidence from Spanish firms (Radicic and Balavac 2019; Vega-Jurado et al. 2009), as well as from Switzerland and the Netherlands (Arvanitis et al. 2015). Similarly, for German firms, Schmiedeberg (2008) and Gesing et al. (2015) find no significant joint effects, with results varying depending on the innovation output measure used.

Regarding other innovation activities beyond internal and external R&D, the present study also finds no evidence of complementarity or substitutability—consistent with the findings of Zhang (2022) for Chinese SMEs. Likewise, this study detects no performance differences by type of cooperation partner, thereby precluding the application of the Oaxaca–Blinder technique to that dimension. Prior evidence from developed economies also remains inconclusive with respect to the differential impact of cooperation according to partner type (Mention 2011; Tödtling et al. 2009; Miotti and Sachwald 2003; among others).

A preliminary explanation for the findings may lie in the combined effect of absorptive capacity—widely recognised as a key factor underlying the synergistic effects of R&D cooperation—and the innovation patterns characteristic of the man-

ufacturing sector under analysis. This interpretation is consistent with Radicic and Balavac (2019), Vega-Jurado et al. (2009), Park et al. (2024), who also emphasise the role of limited absorptive capacity in explaining the absence of such synergistic effects. Accordingly, and building on the low innovation profile outlined in Sect. 3.5, this further highlights that Argentinian manufacturing firms allocate, on average, only 1.35% of their revenue to innovation activities, as reported by ENDEI II (2014–2016)⁹. Since the absorptive capacity depends on internal R&D and non-internal R&D activities (Cohen and Levinthal 1990; Vega-Jurado et al. 2008b; Hervas-Oliver et al. 2012, Zhang 2022), the overall limited innovation investment may account for the absence of synergistic effects observed in this study.

A second explanation for the lack of both direct and indirect effects may relate to the limited scope and intensity of R&D cooperation within Argentina's industrial sector. In line with the weakness of the national innovation system and a limited tradition of collaboration (Albornoz 2009; Lugones et al. 2005; Dutrénit et al. 2019), recent data from the ENDEI II (2014–2016) survey—along with the earlier ENDEI I (2010–2012)—reveal that firms tend to engage less frequently in R&D partnerships, focusing instead on product development, testing, and training. Qualitative features of cooperation—such as duration and depth—are not captured by survey data, despite their known influence on innovation performance (Belderbos et al. 2015; Pucci et al. 2020).

5.2 Main Contributions

Despite growing interest, the literature on complementarity/substitutability exhibits mixed findings and several research gaps. These include limited analysis of R&D cooperation for developing countries, insufficient focus on non-R&D innovation activities, and scarce attention to variations by sector and type of cooperation partner. This paper seeks to address this empirical gap by analysing both the direct effects of R&D cooperation on innovation performance and its potential joint effects with other innovation activities within manufacturing firms in Argentina, introducing novel aspects that contribute to the existing literature.

First, the analysis explores complementarity/substitutability relationships between R&D cooperation and a set of innovation activities that are rarely addressed in the literature and are particularly relevant to firms operating in low-technology sectors (Hansen and Winther 2011; Zhang 2022). The inclusion of these inputs reflects their widespread use by Latin American firms (Crespi and Dutrénit 2014; Dutrénit et al. 2019), particularly within Argentina's industrial sector, as shown in the recent data presented in Table 7 in the Appendix.

A second contribution lies in the exploration of these relationships across different productive sectors and types of cooperation partner. Both analytical dimensions—closely interconnected—have received limited attention in the empirical literature. Sectoral dynamics are incorporated into the analysis through the application

⁹ The large firms allocate 0.28% of their sales revenue to R&D expenses, while in small and medium-sized firms this percentage amounts to 0.15%.

of a new taxonomy specifically tailored to Argentina's innovation context (CIECTI 2020).

Third, this study provides a methodological contribution by applying the Oaxaca–Blinder (OB) decomposition technique (Oaxaca 1973; Blinder 1973; Fortin et al. 2011), a method seldom employed in firm-level innovation analysis. As highlighted earlier in this paper, the OB technique enables the decomposition of the innovation gap into a component attributable to differences in observable firm characteristics and another resulting from differences in the returns to those characteristics. Consequently, this approach offers a novel perspective on the drivers underlying innovation performance.

In addition, the OB technique allows for the examination of both the direct effect of R&D cooperation and its complementarity or substitutability relationships, through comparisons of coefficients for various innovation activities (e.g. internal R&D, training) across firm groups (e.g. cooperating vs. non-cooperating). It assesses both the statistical significance and the magnitude of these differences, while also incorporating scale effects based on firms' average endowments. In this way, the OB decomposition offers a promising alternative for overcoming the limitations of traditional approaches commonly used in the literature. Empirical studies on complementarity/substitutability relationships typically rely on econometric approaches based on interaction terms, which are subject to multicollinearity and pose interpretative challenges—particularly in nonlinear models—or on the supermodularity framework, which addresses some of these limitations but remains constrained by limited data and complexity when analysing multiple innovation activities (Barge-Gil and López 2013; Morero and Ortiz 2017; Serrano-Bedia et al. 2018; Zhang 2022).

5.3 Policy Recommendations, Limitations and Guidelines for Future Research

The proposed empirical exercise offers some guidelines for future research and normative implications. Although this study contributes to the empirical literature—particularly through proposing the Oaxaca-Blinder (OB) decomposition technique, rarely applied in innovation research—it is not exempt from limitations that open avenues for future investigation. First, the greater gap in innovation performance observed in favour of firms that cooperate for R&D in the LMLT sectors, motivates further exploration of the factors that condition the impact of R&D cooperation on innovation performance in these sectors. The Argentine LMLT firms indicate that the lack of linkages, specifically, with S&T agencies, is a main limitation to incorporate new technology and thus, an obstacle to innovation (CIECTI 2013). The potential increasing innovation opportunities for natural resources industries coming from the incorporation of new technologies, such as ICT, biotechnology, nanotechnology, and new materials (Pérez 2010; Dantas et al. 2013), is an additional reason to further analyse cooperation in these sectors.

Second, the results suggest the influence of idiosyncratic, unobservable firm-level factors and omitted variables. As Zhang (2022) notes, although many studies on innovation complementarity rely on cross-sectional data (e.g., Gesing et al. 2015; Serrano-Bedia et al. 2018; Zhang 2022), the use of panel data in future research

could provide a more refined understanding by capturing unobserved firm-level heterogeneity, thereby reinforcing the econometric framework. Moreover, following Gesing et al. (2015), qualitative studies could provide valuable guidance in identifying and introducing variables that capture firm-level heterogeneities, contributing to the development of more robust quantitative models. Future research could also benefit from comparative, cross-national studies applying the Oaxaca-Blinder technique to assess the extent to which the results are influenced by country-specific innovation environments. Third, as the survey data used are not collected annually, does not allow for the capture of potential lagged effects of R&D cooperation on the innovation process. A promising avenue for further analysis based on Oaxaca-Blinder methodology would therefore be to exploit the advantages of a panel data structure with multiple time periods for another developing country.

Four, although this study employs dichotomous variables to represent innovation activities, the method OB still allows for the capture of scale effects, as the coefficient differences associated with each activity are weighted by the average values of the firms engaging in them. Nevertheless, to better align with the existing empirical literature, future research could incorporate continuous variables to more accurately capture these effects. In the present study, dichotomous variables were selected to mitigate potential issues related to multicollinearity.

The findings suggest policy implications, highlighting that programs adapted from successful ones in other regions do not adequately consider local economic, social, governance, and political conditions. (Dutrénit et al. 2019; Arocena and Sutz 2020). Given the role attributed in the literature to absorptive capacity in enabling firms to benefit from external knowledge through cooperation, as well as the contribution of both R&D and non-R&D innovation activities in supporting this capacity, the results found highlight the need to formulate innovation policy schemes that promote both cooperation and the firm absorptive capacity. Although, intensifying cooperation is one of the objectives pursued by Argentina's science, technology and innovation policy since the 2000s, these efforts must be combined with effective policies to increase innovation spending at the firm level. In their study on the effectiveness of the fiscal incentive policy for innovation implemented in Argentina since 1998, and in force today, Crespi et al. (2016) find that actual increase in private sector R&D spending might be lower than the amount of the subsidy, in which case partial crowding-out might not be ruled out. Formulating an integrated policy framework is challenging within an institutional context characterised by the coexistence of institutions aligned with different policy approaches (supply-side, demand-side, systemic), as well as by the proliferation of programmes with highly diverse designs (Dutrénit et al. 2019; Arocena and Sutz 2020).

A second policy recommendation consists of improving statistical information at the national level. Obtaining detailed information on cooperation in Latin America is relevant to design policies with greater impact (Lugones et al. 2003; Suzigan et al. 2009). The questionnaire used in the underlying firm-level dataset is limited to asking if the firm cooperated for R&D with different partners. In this way, the questionnaire does not include additional questions regarding frequency of interactions, duration, continuity, the type of knowledge involved in the cooperation relationship. From this perspective, the observation by Lugones et al. (2003) remains particularly significant:

it is much easier to compute the interactions between agents than to evaluate their quality; it is assumed that there is transfer of knowledge in these interactions, but in reality it is not possible to determine how much is transferred, nor how much it is assimilated.

6 Appendix

Table 6 Classification of Argentine manufacturing sectors based on technology. (Source: Own elaboration based on CIECTI (2020) and OECD (2011))

Industries ISIC Rev. 3	CIECTI (2020)	OECD (2011)
Pharmaceuticals 2423	HMHT	HMHT
Medical, precision and optical instruments 33	HMHT	HMHT
Manufacture of domestic appliances n.e.c. 2930	HMHT	HMHT
Manufacture of special-purpose machinery 292 excl. 2921	HMHT	HMHT
Rubber and plastics products 25	HMHT	LMLT
Other non-metallic mineral products 26	HMHT	LMLT
Electrical machinery and apparatus, n.e.c. 31	LMLT	HMHT
Radio, TV and communications equipment 32		
Motor vehicles, trailers and semi-trailers 34	LMLT	HMHT
Chemicals excluding pharmaceuticals 24 excl. 2423	LMLT	HMHT
Railroad equipment and transport equipment, n.e.c. 352 + 359	LMLT	HMHT
Machinery and equipment, n.e.c. 29	LMLT	HMHT
Manufacture of agricultural and forestry machinery 2921	LMLT	HMHT
Basic metals and fabricated metal products 27–28	LMLT	LMLT
Wood, pulp, paper, paper products, printing and publishing 20–22	LMLT	LMLT
Food products, beverages 15	LMLT	LMLT
Textiles, textile products, leather and footwear 17–19	LMLT	LMLT
Manufacture of furniture; manufacturing n.e.c. 36	LMLT	LMLT

HMHT high and medium-high technology sectors, *LMLT* low and medium-low technology sectors

Table 7 Endowments (Source: Own elaboration based on ENDEI II survey)

Independent variables	Full sample						HMHT sectors						LMLT sectors					
	Group A		Group B		Group A		Group B		Group A		Group B		Group A		Group B			
	Cooperating firms	Non-cooperating firms	Cooperating firms	Non-cooperating firms	Cooperating firms	Non-cooperating firms	Cooperating firms	Non-cooperating firms	Cooperating firms	Non-cooperating firms	Cooperating firms	Non-cooperating firms	Cooperating firms	Non-cooperating firms	Cooperating firms	Non-cooperating firms		
Size	758	3,122	4,0566	3,122	3,5453	178	3,8888	599	3,5957	580	4,1081	2,523	3,5334	588	0,1276	2,552	0,0709	
Foreign	768	3,158	0,1146	3,158	0,0754	180	0,0722	606	0,0941	588	0,1276	2,552	0,0709	588	0,4813	2,552	0,2469	
Export	768	3,158	0,5078	3,158	0,2745	180	0,5944	606	0,3911	588	0,4813	2,552	0,2469	588	0,4643	2,552	0,1857	
Frequency	768	3,158	0,4792	3,158	0,2071	180	0,5278	606	0,2970	588	0,4643	2,552	0,1857	588	0,3690	2,552	0,4855	
Age	768	3,158	0,3659	3,158	0,4690	180	0,3556	606	0,3993	588	0,3690	2,552	0,4855	588	0,7551	2,552	0,2911	
Internal R&D	768	3,158	0,7669	3,158	0,3227	180	0,8056	606	0,4554	588	0,7551	2,552	0,2911	588	0,3724	2,552	0,1062	
External R&D	768	3,158	0,3789	3,158	0,1127	180	0,4000	606	0,1403	588	0,3724	2,552	0,1062	588	0,7381	2,552	0,3644	
Design & eng	768	3,158	0,7565	3,158	0,3920	180	0,8167	606	0,5083	588	0,7381	2,552	0,3644	588	0,2364	2,552	0,0878	
Tech. transfer	768	3,158	0,2552	3,158	0,0950	180	0,3167	606	0,1254	588	0,2364	2,552	0,0878	588	0,8452	2,552	0,5435	
ME & ICT	768	3,158	0,8555	3,158	0,5633	180	0,8889	606	0,6469	588	0,8452	2,552	0,5435	588	0,6497	2,552	0,2947	
Training	768	3,158	0,6601	3,158	0,3151	180	0,6944	606	0,4010	588	0,6497	2,552	0,2947	588	0,4796	2,552	0,2712	
Financing	768	3,158	0,4948	3,158	0,2891	180	0,5444	606	0,3647	588	0,4796	2,552	0,2712	588	0,7585	2,552	0,4161	
Market inf. sources	768	3,158	0,7669	3,158	0,4398	180	0,7944	606	0,5396	588	0,7585	2,552	0,4161	588	0,3878	2,552	0,0658	
S&T inf. sources	768	3,158	0,3919	3,158	0,0731	180	0,4056	606	0,1040	588	0,3878	2,552	0,0658	588	0,7619	2,552	0,3844	
Available inf	768	3,158	0,7695	3,158	0,4028	180	0,7944	606	0,4802	588	0,7619	2,552	0,3844	588	—	—	—	
Tech. intensity	768	3,158	0,2344	3,158	0,1919	—	—	—	—	—	—	—	—	—	—	—	—	

Mean of independent variables by group of firms
Full sample and industrial sector subsamples

Table 8 Coefficients. (Source: Own elaboration based on ENDEI II survey)

Dependent variable:	Full sample						HMHT sectors						LMLT sectors					
	Group A		Group B		Group A		Group B		Group A		Group B		Group A		Group B			
	Cooperating firms	S.E.	Non-cooperating firms	S.E.	Cooperating firms	S.E.	Non-cooperating firms	S.E.	Cooperating firms	S.E.	Non-cooperating firms	S.E.	Cooperating firms	S.E.	Non-cooperating firms	S.E.		
Independent variables	Odds Ratio		Odds Ratio	S.E.	Odds Ratio		Odds Ratio	S.E.	Odds Ratio		Odds Ratio	S.E.	Odds Ratio		Odds Ratio	S.E.		
Size	0.9496	0.1915	0.9896	0.0578	1.9467	1.0160	0.9767	0.1547	0.8439	0.1913	0.9939	0.0618	0.8439	0.1913	0.9939	0.0618		
Foreign	0.6521	0.3786	0.8202	0.1825	Omitted	Omitted	1.3176	0.8184	0.5648	0.3503	0.7352	0.1752	0.5648	0.3503	0.7352	0.1752		
Export	1.7901	0.8026	1.2536	0.1740	0.7919	0.7859	1.7012	0.5911	2.5074*	1.3599	1.1789	0.1796	2.5074*	1.3599	1.1789	0.1796		
Frequency	1.5352	0.7966	1.3770*	0.2557	1.2444	1.7814	2.7683**	1.3983	1.9411	1.2105	1.1925	0.2351	1.9411	1.2105	1.1925	0.2351		
Age	0.7653	0.3261	0.9471	0.1048	0.6924	0.7063	1.2880	0.3971	0.6312	0.3140	0.9168	0.1089	0.6312	0.3140	0.9168	0.1089		
Internal R&D	2.3550**	1.0200	4.0964***	0.8108	2.6795	3.3613	1.3689***	7.6128	2.2123*	1.0421	3.2451***	0.6850	2.2123*	1.0421	3.2451***	0.6850		
External R&D	0.8822	0.4623	1.7522	0.6048	1.6178	2.4819	2.0484	2.2796	0.7625	0.4647	1.5851	0.5621	0.7625	0.4647	1.5851	0.5621		
Design & eng	0.7458	0.4712	1.7851***	0.2703	0.9131	1.5876	1.6640	0.6567	0.6879	0.5003	1.7342***	0.2859	0.6879	0.5003	1.7342***	0.2859		
Tech. transfer	1.4094	1.0723	2.3170***	0.7286	0.1598	0.2037	1.3830	0.8526	3.7004	4.6826	2.9886***	1.1481	3.7004	4.6826	2.9886***	1.1481		
ME & ICT	4.1695***	2.1829	2.5088***	0.3500	1.8077	2.5341	1.8168	0.6933	5.3087***	3.0548	2.7463***	0.4150	5.3087***	3.0548	2.7463***	0.4150		
Training	2.0334	1.0828	1.4281**	0.2532	2.0519	1.6132	1.6604	0.7394	2.0419	1.3246	1.4057*	0.2721	2.0419	1.3246	1.4057*	0.2721		
Financing	1.3140	0.6956	1.4259**	0.2367	2.3794	2.1964	1.6424	0.7336	1.3604	0.8350	1.3500*	0.2434	1.3604	0.8350	1.3500*	0.2434		

Table 8 (Continued)

Dependent variable:	Full sample				HMHT sectors				LMLT sectors			
	Group A	Cooperating firms	Group B	Non-cooperating firms	Group A	Cooperating firms	Group B	Non-cooperating firms	Group A	Cooperating firms	Group B	Non-cooperating firms
Independent variables	Odds Ratio	S.E.	Odds Ratio	S.E.	Odds Ratio	S.E.	Odds Ratio	S.E.	Odds Ratio	S.E.	Odds Ratio	S.E.
Market inf. sources	3.5673***	1.4165	5.1099***	0.7495	9.3922**	9.2191	5.4428***	1.8944	3.0905**	1.3618	5.0900***	0.8327
S&T inf. sources	1.0012	0.4631	0.7942	0.2874	2.6155	4.3497	0.2730	0.2338	0.8882	0.4800	1.0772	0.4447
Available inf	3.0356***	1.2230	3.0710***	0.4915	0.6420	0.6585	3.4107***	1.4683	4.6529***	2.0908	2.9746***	0.5105
Tech. intensity	1.2887	0.7654	0.8690	0.1254	–	–	–	–	–	–	–	–
_cons	0.7913	0.6598	0.2604	0.0570	0.2484	0.5013	0.1739	0.0991	1.0170	0.9250	0.2715***	0.0638
Number of obs	758		3122		165		599		580		2523	
Wald chi2	115.52		773.53		47.72		161.68		83.13		621.08	
Prob> chi2	0.0000		0.0000		0.0000		0.0000		0.0000		0.0000	
Log pseudolikelihood	-101.31401		-1088.2337		-19.752077		-155.44112		-75.171121		-937.32171	
Pseudo R2	0.3865		0.4600		0.3182		0.5525		0.4429		0.4416	

Odds-Ratio. Logistic regression model results by group of firms. Full sample and industrial sector subsamples

Export is dropped from model 1 in HMHT sectors since this variable predicts success perfectly

Robust standard errors

* p -value ≤ 0.10 ** p -value ≤ 0.05 *** p -value ≤ 0.01

Table 9 Wald tests based on Logistic regression in Table 8 for full sample and industrial sector subsamples. (Source: Own elaboration based on ENDEI II survey)

	Wald χ^2 (df = 1)		
	Full sample	HMHT sectors	LMLT sectors
Internal R&D	1.36 <i>p</i> -value: 0.2440	1.42 <i>p</i> -value: 0.2336	0.55 <i>p</i> -value: 0.4577
External R&D	1.22 <i>p</i> -value: 0.2703	0.02 <i>p</i> -value: 0.9007	1.08 <i>p</i> -value: 0.2991
Design & Eng	1.74 <i>p</i> -value: 0.1876	0.11 <i>p</i> -value: 0.7358	1.54 <i>p</i> -value: 0.2147
Tech. Transfer	0.40 <i>p</i> -value: 0.5249	2.33 <i>p</i> -value: 0.1267	0.03 <i>p</i> -value: 0.8716
ME & ICT	0.85 <i>p</i> -value: 0.3558	0.00 <i>p</i> -value: 0.9972	1.23 <i>p</i> -value: 0.2676
Training	0.36 <i>p</i> -value: 0.5495	0.06 <i>p</i> -value: 0.8144	0.30 <i>p</i> -value: 0.5811
_cons	1.56 0.2120	0.02 <i>p</i> -value: 0.8818	1.86 <i>p</i> -value: 0.1723

* *p*-value \leq 0.10 ***p*-value \leq 0.05 ****p*-value \leq 0.01

Table 10 Correlation matrix for full sample using Cramér's V and R². (Source: Own elaboration based on ENDEI II survey)

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Inno.tech (1)	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Size (2)	0.0290	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Foreign (3)	0.0572	0.0792	1	-	-	-	-	-	-	-	-	-	-	-	-	-
Export (4)	0.2199	0.1135	0.2031	1	-	-	-	-	-	-	-	-	-	-	-	-
Frequency (5)	0.3126	0.0403	0.1012	0.2326	1	-	-	-	-	-	-	-	-	-	-	-
Age (6)	-0.0417	0.0754	-0.1268	-0.1778	-0.0612	1	-	-	-	-	-	-	-	-	-	-
Internal R&D (7)	0.4846	0.0323	0.0582	0.2788	0.4263	-0.0652	1	-	-	-	-	-	-	-	-	-
External R&D (8)	0.2581	0.0151	0.0622	0.1729	0.2491	-0.0383	0.3869	1	-	-	-	-	-	-	-	-
Design & eng. (9)	0.4712	0.0563	0.1017	0.2700	0.3452	-0.0926	0.4809	0.2859	1	-	-	-	-	-	-	-
Tech. Transfer (10)	0.2184	0.0434	0.1366	0.1741	0.2112	-0.0566	0.2265	0.2451	0.2435	1	-	-	-	-	-	-
ME & ICT (11)	0.5836	0.0422	0.0701	0.2116	0.3384	-0.0330	0.4346	0.2650	0.4937	0.2345	1	-	-	-	-	-
Financing (12)	0.3451	0.0158	-0.0196	0.1184	0.1992	0.0011	0.2902	0.1927	0.2901	0.1757	0.4780	1	-	-	-	-
Market inf. sources (13)	0.5674	0.0212	0.0371	0.1962	0.2935	-0.0317	0.4453	0.2401	0.4483	0.1896	0.5213	0.3254	1	-	-	-
S&T inf. Sources (14)	0.2221	0.0358	0.0941	0.1794	0.2565	-0.0864	0.2953	0.2547	0.2398	0.1636	0.2344	0.1567	0.2344	1	-	-
Available inf. (15)	0.5327	0.0213	0.0002	0.1911	0.3428	-0.0286	0.4568	0.2406	0.4364	0.1940	0.5104	0.2979	0.5680	0.3309	1	-
Tech. Intensity (16)	0.0853	0.0001	0.0103	0.1280	0.1032	-0.0595	0.1290	0.0475	0.1167	0.0678	0.0854	0.0828	0.0943	0.0546	0.0782	1

Cramér's V applied to measure associations between binary variables
R² applied to measure associations between a continuous variable and a binary variable

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Data Availability The data that support the findings of this study are not available online. The dataset is available on request from the Ministry of Science, Technology and Innovation of Argentina.

Conflict of interest C. Pasciaroni declares that she has no competing interests.

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