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R&D Subsidies as Dual Signals in Technological Collaborations

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ABSTRACT

We investigate the influence of public R&D subsidies on a firm's likelihood to form technological collaborations. Using signaling theory, we conceptualize the award of a subsidy as a pointing signal (i.e., indicating a quality attribute that distinguishes the signaler from its competitors), and the monetary amount raised through a subsidy as an activating signal (i.e., activating the quality attribute of the signaler). Drawing on the attention-based view, we investigate whether the relative salience of these signals varies between two types of signal receivers: academic and corporate partners. Using a panel sample of Spanish manufacturing firms, our results indicate that the two types of receivers attend to the two signals differently: while academic partners attend to pointing signals only (sent by the award of a selective subsidy), corporate partners react to the richer information that activating signals provide (sent by the monetary value of both selective and automatic subsidies). Our results are stronger for SMEs vis-à-vis large firms, and hold after controlling for endogeneity, selection bias, simultaneity, attrition, inter-temporal patterns in technological collaborations, and the substantive effects of subsidies. The theorized and tested dual nature of subsidy-enabled signals and their different salience to distinct partner types hold interesting implications for research on alliances, innovation policy, and signals.

1. Introduction

This study investigates the influence of public R&D subsidies on the likelihood of recipient firms forming technological collaborations. While the main intent of subsidies is to raise private R&D investments and outputs toward the social optimum, the promotion of collaborative innovation approaches has become a key complementary goal for policymakers (Colombo et al., 2009; Hottenrott and Lopes-Bento, 2014). As innovation increasingly requires complex knowledge distributed in multiple value chains, the stimulus of collaborative R&D activities provides social and economic benefits by fostering positive externalities within and across industries, and the collaborating economic agents' internalization of knowledge spillovers (Sampson, 2007).

However, several welfare-enhancing R&D collaborations are not formed due to the high transaction costs in markets for technologies (Gulati, 1999). Information asymmetries encourage parties to overstate the value of their contribution to the potential collaboration, particularly when technological resources are highly uncertain and idiosyncratic (Teece, 1986). Appropriability hazards during negotiation lead to the risk of opportunistic behaviors and knowledge expropriation (Arrow, 1996). Consequently, a double self-selection-out process might ensue: highly innovative firms are discouraged from seeking value-creating collaboration opportunities, and partners abstain from joining forces with them. This untapped collaboration potential represents a policy problem.

Do public R&D subsidies favor collaborative behavior? This question is at the core of the innovation policy evaluation literature that focuses on behavioral additionality (Chapman et al., 2018),[1] and scholars have hitherto offered mixed answers. Most studies report an average positive association between subsidies and technological collaborations (e.g., Busom and Fernández-Ribas, 2008; Grilli and Murtinu, 2018). However, Colombo et al. (2006) and Hsu (2006) find a negative relation, while Chapman et al. (2018) find differential effects of R&D subsidies on collaborative behaviors

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[1] Behavioral additionality refers to changes in a firm's behavior that would not have occurred in the absence of public support (Autio et al., 2008). The focus of this study, engagement in R&D collaborations, is one of the different policy-induced behaviors investigated in the literature; other examples are organizational learning, skills acquisition, and project scale-up (Clarysse et al., 2009; Georghiou and Clarysse, 2006). These behavioral changes represent the so-called "second-order additionalities", that is, the indirect impact of public support. However, the bulk of empirical studies evaluating policy measures focuses on "first-order additionalities", that is, the direct impact of public support in terms of input additionality (i.e., changes in private R&D investments) and output additionality (i.e., changes in innovative outputs, such as patents and new products) (Cerulli et al., 2016).

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across firms. A reason for such ambiguous evidence is the aggregate nature of data and related measures, as most studies model subsidies as a binary variable (Cerulli et al., 2016; Miotti and Sachwald, 2003), without taking into account the subsidy amount and disentangling different forms of subsidies (for an exception see, for instance, Colombo et al., 2011).[2]

The present study aims to provide a finer-grained analysis of the association between R&D subsidies and technological collaborations. Using the signaling theory lens, we (additionally) take into account the amount of public funding awarded to firms for their innovation activities, which is almost absent in previous works.[3] Similarly to other signals investigated in prior research on technological collaborations, such as patents, initial public offerings, and the presence of star scientists (Luo et al., 2009; Pollock and Gulati, 2007), subsidies may be credible signals of the (latent and difficult to observe) quality of a firm's innovation (Lerner, 1999). These signals help reduce the perceived uncertainty of the firm's viability as a partner, ultimately facilitating collaboration formation.

Differently from previous studies that conceptualize subsidies as a single monolithic signal, we argue that: i) the award of a subsidy (independently of its value), and ii) the monetary amount raised through a subsidy convey different information, with the latter communicating more on the innovating firm's merit and potential. Using the definitions that Connelly et al. (2011) proposed, we posit that the award of a subsidy is a *pointing signal*, as it indicates a characteristic (the quality and innovation potential) that distinguishes the signaler from its competitors, whereas the amount raised through a subsidy is an *activating signal*, indicating not only the characteristic distinguishing the signaler, but activating the quality characteristic of the signaler. In fact, external financial resources allow the firm to acquire key inputs to the R&D process that help transform the innovation potential into new products or services. We thus investigate whether the salience of these signals varies between two types of receivers (academic and corporate partners) due to their different nature, goals, and resultant attention to external stimuli.[4] We hence respond to Pollock and Gulati's (2007) call for further research on whether distinct types of collaboration partners are influenced to a greater or lesser degree by different signals.

To this end, we use a seven-year (2001–2007) panel sample of Spanish manufacturing firms. Our analysis focuses on R&D collaborations (hereafter collaborations), which are a non-equity and the most diffused form of technological alliance (Gudergan et al., 2012; Hagedoorn, 2002),[5] including both forms of Spanish public authorities' R&D subsidy programs (i.e., competitive selective subsidies and automatic subsidies in the form of R&D tax credits). Differently from prior works that focus on a single policy measure (e.g., Bronzini and Piselli, 2016; Howell, 2017), or on small and medium enterprises (hereafter SMEs) (e.g., Islam et al., 2018), our dataset offers heterogeneity in signals, signalers, and receivers, thus supporting a more nuanced understanding of the phenomenon.

Our results indicate that the kind of information that matters for signaling critically depends on the signal receiver type. In other words, academic and corporate partners attend differently to the signals that public R&D subsidies emit. On the one hand, the award of a selective subsidy, independently of its amount, increases the likelihood of collaboration formation with universities, meaning that this partner type attends and reacts to a *pointing signal*. On the other hand, corporate partners attend to and react only to the richer information that the financial value of selective and automatic subsidies provides via the *activating signal*: the larger the subsidized amount, the more likely the collaboration with other firms. Both relations are stronger for SMEs than large firms. The theorized and tested dual nature of subsidy-enabled signals and their different salience to distinct partner types hold interesting implications for research on alliances, innovation policy, and signals.

The paper is structured as follows. The next section reviews the relevant literature, while Section 3 develops the conceptual framework. Sections 4 and 5 describe the data and the methodology, respectively. Section 6 presents the findings, and the final section discusses our contributions to research, policy and practice, outlining the limitations and avenues for future research.

2. Literature review

The innovation policy literature has mainly evaluated public R&D subsidies in terms of input and output additionality (e.g., Beck et al., 2016; Czarnitzki and Lopes-Bento, 2013), while behavioral additionality, and particularly firms' collaborative behavior, has received less attention (Chapman et al., 2018), notwithstanding its theoretical relevance and the growing popularity of collaborative innovation in practice (Georghiou and Clarysse, 2006).

Table 1 provides an overview of the main studies that have investigated the relationship between R&D subsidies and collaborations.[6] Each work is described in terms of the sample used (most studies use cross-sectional data and focus on European countries), the measurement of core variables (subsidies are largely modelled with binary indicators, which some studies use as controls), and key findings. While two studies (Hsu, 2006; Colombo et al., 2006) find a negative relationship, the majority report no or positive relations. Falk (2007) shows that a single policy intervention is not enough to trigger more collaborative behavior, but that two or more are needed, suggesting the cumulative nature of behavioral additionality and the importance of longitudinal empirical designs to analyze the phenomenon.

A key discriminating factor is the nature of the collaboration partner. Most studies show that subsidies encourage collaborations with academic partners, while the evidence on collaborations with corporate partners is mixed. While Arranz and De Arroyabe (2008), Maietta (2015), and Grilli and Murtinu (2018) find a positive effect of public funding on corporate collaborations, Afcha (2011) and Miotti and Sachwald (2003) do not find such an effect on collaborations with suppliers and customers. Some studies analyze collaboration breadth, measured as the number and relevance of partner types with which a firm cooperates: Cerulli et al. (2016) and Chapman et al. (2018) agree on the existence of a positive influence of subsidies, while Cano-

[2] Colombo et al. (2011) consider two different forms of R&D subsidies: automatic and selective schemes. Automatic schemes provide financial assistance to all applicants fulfilling the requirements specified by law. Selective schemes provide financial support to chosen applicants who compete for a subsidy and whose innovative projects are judged by committees of experts appointed by the government (Colombo et al., 2011; Grilli and Murtinu, 2018). Many automatic schemes are in the form of R&D tax credits, and many selective schemes are grants, but this is not always the case (see, for instance, Armstrong, 2001 and Harris, 1991). No common definition of subsidy exists, and whether the definition should include automatic schemes is under debate (see, for instance, https://www.wto.org/english/res_e/booksp_e/anrep_e/wtr06-2b_e.pdf). In this work, our definition of subsidy encompasses automatic schemes in the form of tax credits (for a similar approach see, for instance, Aldy et al., 2018; Colombo et al., 2011; Czarnitzki et al., 2011).

[3] Hottenrott et al. (2017) and Howell (2017) are two exceptions. These studies, however, investigate input and output additionality, respectively, and not behavioral additionality. Moreover, in the SBIR program examined in Howell (2017), all grantees in a given year receive the same amount from the U.S. Department of Energy; thus, the amount does not discern a firm's ability to attract public funding.

[4] For more details on salience see, for instance, Bordalo et al. (2012, 2015).

[5] The focus on non-equity alliances hinges on the fact that signals are more important than in the case of equity alliances (for a similar approach see, for instance, Busom and Fernandez-Ribas, 2008). As explained, for instance, by Lui and Ngo (2004), information asymmetries and opportunism in equity alliances are likely to be lower than in non-equity ones, which lack the ownership and equity function in controlling and aligning the incentives between partners (Gudergan et al., 2012; Gulati, 1995).

[6] We acknowledge that the literature streams on policy evaluation and collaborations are extensive and comprise studies that have not been reviewed in this work, since we focus on those that specifically examine the subsidy-collaboration relationship at the core of our study.

Table 1
Existing studies on the relationship between public subsidies and collaborations.

Study	Sample (location; time)	Variables	Key findings
Miotti and Sachwald (2003)	Cross-sectional data on 4215 manufacturing firms (France; 1994–1996)	Public funding: binary Collaboration: binary (distinguishing partner type)	Positive relation between funding and collaboration with academic partners and competitors, but no significant relation between funding and collaboration with suppliers and customers.
Mohnen and Hoareau (2003)	Cross-sectional data on 9191 manufacturing and service firms (France, Germany, Ireland, Spain; 1994–1996)	Public funding: binary Collaboration: binary	Positive relation between public funding and collaboration with academic partners.
Wong and He (2003)	Cross-sectional data on 132 manufacturing firms (Singapore; 2000)	Public funding: binary Collaboration: factor measuring collaboration intensity with different partner types Moderator: internal pro-innovation climate (factor)	Positive relation between funding and collaboration with knowledge sources (academia and consultants), which is stronger for firms with a promotive internal climate. No significant relation between funding and collaboration with industrial players.
Belderbos et al. (2004)	Lagged data on 2149 innovating firms (The Netherlands; 1996–1998).	Public funding: binary (control variable) Collaboration: binary (distinguishing partner type)	Positive relation between funding and collaboration with academic partners and with suppliers and customers (but not with competitors). The relation turns insignificant when restricting the sample to only firms that are new to collaboration.
Negassi (2004)	Panel data on 1763 innovating firms (France; 1990–1996)	Public funding: binary Collaboration: intensity measured as the budget that a firm allots to collaboration	Positive relation between public subsidies and collaboration intensity.
Colombo et al. (2006)	Panel data on 420 new technology-based firms (Italy; 1994–2003)	Public funding: binary (control variable) Collaboration: binary (equal to 1 if the firm's first alliance is technological)	Negative weakly significant relation between funding and the formation of technological alliances.
Hsu (2006)	Cross-sectional data on 696 start-ups (USA; 1988–1999)	Public funding: binary Collaboration: count number of R&D alliances	SBIR funded start-ups have a lower likelihood of establishing R&D alliances than those backed by venture capitalists.
Falk (2007)	Cross-sectional data on 937 manufacturing and service firms (Austria; 2004)	Public funding: count number of subsidies awarded Collaboration: binary	Support from a single scheme does not trigger new collaborations. Only support from two or more schemes does.
Arranz and De Arroyabe (2008)	Cross-sectional data on 1652 manufacturing firms that have engaged in innovation (Spain; 1997)	Public funding: binary Collaboration: binary (distinguishing partner type)	Positive relation between funding and collaboration with any partner type.
Busom and Fernández-Ribas (2008)	Cross-sectional data on 716 manufacturing firms reporting positive R&D expenditures (Spain; 1999)	Public funding: binary Collaboration: binary (distinguishing partner type) Moderator: international patents (binary)	Positive relation between funding and collaboration with academic partner. The weaker positive relation between funding and collaboration with suppliers and customers is magnified if the firm owns international patents.
Segarra-Blasco and Arauzo-Carod (2008)	Cross-sectional data on 4150 manufacturing and service firms with at least one innovation (Spain; 1998–2000)	Public funding: binary Collaboration: binary (distinguishing partner type)	Positive relation between funding and collaboration with academic partners.
Afcha (2011)	Panel data on 1136 manufacturing firms (Spain; 1998-2005)	Public funding: binary Collaboration: binary (distinguishing partner type)	Positive relation between funding and collaboration with academic partners, but no significant relation between funding and collaboration with suppliers and customers.
Kang and Park (2012)	Panel data on 147 biotech SMEs (South Korea; 2005-2007)	Public funding: binary Collaboration: count number of collaborations (distinguishing partner type)	Positive relation between funding and collaborations with both academic and corporate partners (but only if the partners are domestic).
Maietta (2015)	Panel data on 1744 food and drink firms (Italy; 1995–2006)	Public funding: binary Collaboration: binary (distinguishing partner type)	Positive relation between funding and collaborations with all partner types.
Cerulli et al. (2016)	Panel data on manufacturing and services firms, for a total of 1090 observations (Italy; 1998–2000 and 2002–2004)	Public funding: binary Collaboration: breadth measured as the number of partner types weighted by their relevance	Positive relation between funding and collaboration breadth.
Cano-Kollmann et al. (2017)	Cross-sectional data on 5133 manufacturing and service firms (29 European countries; 2007)	Public funding: rank-ordering variable counting different types of funding schemes Collaboration: rank-ordering variable counting different partner types Moderation: experience in innovation activity	No significant relation between funding and number of open innovation partners. Only subsidies (and not tax breaks) show a positive significant relation with the number of open innovation partners, and only in firms with no experience in innovation.
Chapman et al. (2018)	Cross-sectional data on 5371 manufacturing and service firms (Spain; 2002-2010 and 2007–2013)	Public funding: binary Collaboration: breadth measured as the number of partner types Moderator: collaboration experience	Average positive relation between funding and collaboration breadth, which is magnified by collaboration experience. Evidence of differential impacts from subsidy award: 56% of subsidized firms experience an increase in collaboration breadth, 13% experience no impact, and 31% experience a negative impact.
Grilli and Murtinu (2018)	Cross-sectional data on 902 new technology-based firms (Italy; 1999-2008)	Public funding: binary Collaboration: binary (distinguishing partner type) Moderators: technical education and industry-specific work experience of the founding team	Positive relation between funding and collaborations with both academic and corporate partners. Industry-specific work experience of the founding team positively moderates the relation between funding and collaboration with corporate partners.

Kollmann et al. (2017) find no significant evidence of this.

Several studies find that the relationship between public subsidies and collaboration formation depends on moderating factors. Experience in collaborative agreements is one of these. Chapman et al. (2018) show that this magnifies the positive influence of R&D subsidies on collaboration breadth. When restricting the sample to firms that are new to collaboration, Belderbos et al. (2004) find no association between public funding and R&D cooperation, differently from the positive significant results they find for the whole sample. As regards experience in innovation activity, Cano-Kollmann et al. (2017) find a negative moderating role: public support appears to drive more collaborative behavior in firms that are new to innovation compared to long-time innovators. Grilli and Murtinu (2018) focus on human capital characteristics, showing that the industry-specific work experience of the founding team strengthens the positive relationship between selective subsidies and corporate alliances. Busom and Fernández-Ribas (2008) find a similar role in relation to the firm's ownership of international patents. Finally, Wong and He (2003) indicate that a firm's internal climate that promotes innovation positively moderates the relationship between public R&D support and collaboration behavior.

In light of this mixed evidence, we aim to advance understanding on the relationship between public subsidies and collaborations by combining data on the public funding monetary amount and the signaling perspective, thus offering an original approach to behavioral additionality studies.

3. Conceptual framework

This study's framework draws on signaling theory (Spence, 1973), which is widely used in the management literature (for a review, see Connelly et al., 2011). As in typical signaling models, our framework includes: i) the signal itself (the subsidy), ii) the signaler (the company awarded the subsidy having relevant private information about the quality and innovation potential), and iii) the receiver (the prospective collaboration partner lacking such private information and toward whom the signal is directed).

According to Spence (1973), effective signals that reduce third-party uncertainty and mitigate transaction costs are observable, correlated with the underlying quality of the signaler, and costly to obtain. Signaling occurs when the receiver uses the signal as a surrogate for quality (in our context, the subsidized firm's innovation potential), and makes an informed decision about a certain course of action (in our context, the choice of signaler as a collaboration partner and investment in the resulting collaboration) that is beneficial to the signaler and that the receiver would otherwise not have taken.

In the following, building on the classification of signals according to Connelly and colleagues (2011), we propose the dual nature of the signaling of R&D subsidies. We argue that different characteristics of subsidies convey information that distinct receiver types attend to and interpret differently. In so doing, we aim to shed more light on the complex nature of signals attached to public R&D funding.

3.1. Subsidy award and pointing signals

We propose that the award of a subsidy is a *pointing signal*. By acting as a "stamp of approval" through which governmental bodies certify the awardee's merit, it distinguishes the signaler from its competitors, that is, comparable firms looking for collaboration partners. This is true independently of the amount awarded.

However, the subsidy's ability to act as a *pointing signal* depends on its selective or automatic nature. Selective subsidies have the characteristics of *Spencian* signals to a greater extent than automatic subsidies. First, signal fit, defined as the degree to which the signal is correlated with unobservable quality, is higher for selective subsidies than automatic subsidies. A selective subsidy follows a competitive procedure where a panel of experts scrutinizes rival applications. These experts, appointed by public authorities for their state-of-the-art knowledge of specific technologies and industries, are well positioned to make sound judgments on the merit of innovation projects. While distortions might exist (for instance, due to personal connections and political consensus, e.g., Lerner, 2002), the procedures to allocate selective subsidies are generally well designed and administered, and subsidies are awarded to high-potential applications based on meritorious criteria (Hsu, 2006).[7] Conversely, there is little competition among applicants of tax credits, as it is sufficient to comply with the requirements specified in the procedure (Appelt et al., 2016; Lokshin and Mohnen, 2012).[8]

Second, compared to automatic subsidies, the awarding of selective subsidies is more observable by outsiders. Public institutions dispensing competitive awards typically publicize the list of awardees who might also celebrate by announcing such event on their website or other communication channels (Islam et al., 2018). By contrast, neither the beneficiary firms nor tax authorities are likely to advertise a tax credit event.

Third, signal cost is higher for selective subsidies than automatic subsidies. The application process for selective subsidies is onerous in terms of time and effort, since the candidate firm must provide detailed documentation of the project's content and plans to convince the evaluation committee of its worthiness vis-à-vis competing proposals.[9] These costs, particularly high for low quality firms, reduce the likelihood of false signaling (Bird and Smith, 2005). By contrast, due to their automatic nature and typically more loose eligibility criteria, the tax credit claim process entails less time and lower costs.

For the above reasons, and in line with the results of Colombo et al. (2011), we expect the award of a selective subsidy to act as a stronger *pointing signal* than the award of an automatic subsidy.

3.2. Subsidy amount and activating signals

We contend that the monetary amount raised through a subsidy emits an *activating signal*. Unlike the mere award of a subsidy, the *activating signal* not only distinguishes the signaler from its competitors, but is also critical to activating the quality potential of the signaler. In fact, the financial resources awarded can be productively deployed to acquire and retain key resources that help successfully realize the innovation potential in new commercial products, services, and/or technologies (Eisenhardt and Schoonhoven, 1996).

Differently from the binary nature of *pointing signals*, the strength of *activating signals*, and hence their informative power, varies with the amount of funding awarded. A larger endowment makes the firm more

[7] The success rate in competitive procedures naturally varies across funding programs. For instance, Feldman and Kelley (2006) report that less than 20% of applications to the U.S. Advanced Technology Program at the National Institute of Standards and Technology receive funding every year. Busom and Fernández-Ribas (2008), using data from the Spanish Statistical Institute, mention that only 13% of Spanish innovative firms received public support for R&D activities during the period 1996-1998. Huergo and Moreno (2017), drawing on data from the Centre for the Development of Industrial Technology (CDTI) in the period 2002-2005, highlight that 8.2% of Spanish companies annually received only CDTI public funding, 10.7% only a national subsidy, and 4.3% both CDTI and a national subsidy.

[8] Some automatic subsidy schemes follow a "first-in-first-out logic" where the subsidy is given to all firms that have applied until the allocated budget is exhausted (this is the case, for instance, of some Italian tax credits such as "Industria 4.0"). Thus, there may be implicit competition in applying to the procedure, even though such competition is much lower than that associated with selective procedures. In other cases, e.g., in Spain, the government tends to not define a specific closed budget for automatic subsidy schemes.

[9] Howell (2017) estimates that applying to the competitive SBIR program can take up one to two months of a full-time employee's time. According to Islam et al. (2018), government applications can take ten to twelve weeks of dedicated effort.

attractive to would-be partners, which are more likely to join forces due to the resource contributions the signaler might bring to the collaboration (Hitt et al., 2004; Negassi, 2004).

We argue that this holds whether the liquidity has been obtained through an automatic or a selective subsidy. In principle, the liquidity raised through a selective procedure may be more correlated with the awardee's quality and innovation potential. However, the liquidity raised through automatic subsidies also contains relevant information, as it certifies the amount of a firm's R&D investments. Indeed, to be eligible for automatic subsidies, firms must formalize their R&D activities (Kleinknecht and Reijnen, 1991), which is a particularly significant shift for those firms that pursue innovation informally (Santamaría et al., 2009). Firms claiming tax credits are accountable to public oversight and responsible for periodic investment reporting (Islam et al., 2018).

While the award of an automatic subsidy is unlikely to be publicized *per se* (see Section 3.1), the related liquidity becomes observable, as it directly influences the value of accounting items in the firm's financial statements (balance sheet, income, and cash flow statements) (Lee et al., 2014). In the screening and due-diligence phases of the alliance formation process, these documents are typically reviewed by prospective partners (Dacin et al., 1997; Dyer et al., 2001), and the "accounting effects" of the awarded amounts (obtained through both selective and automatic schemes) are combined in different parts of the financial statements (Chen and Wang, 2004)[10], making such statements more solid and attractive to potential collaboration partners.

We therefore argue that in the case of *activating signals*, the distinction between selective and automatic subsidization schemes becomes less relevant than in the case of *pointing signals*.

3.3. The salience of signals for different receiver types

The salience of the above signals may vary depending on the type of receiver (Pollock and Gulati, 2007), which in our context refers to potential collaboration partners. The distinct nature and goals of academic and corporate partners may explain their different attention and reaction to the two signals. In decision making on collaboration formation, we propose that the award of a subsidy (*pointing signal*) suffices to influence the choice of prospective academic partners, but not that of corporate partners who require the additional information that the subsidized amount conveys (*activating signal*).

This reasoning is based on the attention-based view (Ocasio, 1997). According to this view, being exposed to the vast amount of information potentially conveyed by signals, and having limited attention due to time and processing power constraints, receivers selectively attend to a restricted number of *stimuli* from the environment, which are typically goal-related (Hirshleifer and Teoh, 2003). As they pertain to distinct domains (science and business, respectively), universities and corporate players have different motivations for initiating collaborations (Okamuro et al., 2011).

The main goals of academic institutions are typically scientific advancement and technology transfer, with relatively less interest in market applications (Bird and Smith, 2005). Academic institutions primarily look for partners possessing advanced technical knowledge, thus pledging their academic know-how to enable the development of an innovation that would otherwise not be realized (Bercovitz and Feldman, 2007; Mohnen and Hoareau, 2003). Therefore, academic institutions might consider the *pointing signal* informative enough: carrying the certification of public authorities, the award of a subsidy, particularly if selective, helps discriminate firms with the required level of technical knowledge from those without such knowledge. Conversely, for corporate players, scientific goals might be important but only as a means to achieve market-related ones. Corporates are primarily concerned with the commercial exploitation of the technological outcomes of the collaboration, which crucially depend on the counterparty's contribution (Cappelen et al., 2012; Colombo et al., 2006). When evaluating both the collaboration and the partner's viability, corporate players seek information not only on technical mastery, but also on market potential. Howell (2017) shows that subsidized firms typically use the awarded money to develop prototypes and/or minimum viable products, and carry out activities that bring the innovation closer to the market. Industrialization and commercialization activities account for a large share of total development expenditures, often more than half (Cooper and Kleinschmidt, 1988; Frattini et al., 2014). We thus posit that corporate players may find *activating signals* more salient, being better aligned with their goals; further, their attention to *activating signals* grows as the subsidized amount increases.

Another reason why academic institutions may find *pointing signals* more salient (while corporates only react to the additional information conveyed by *activating signals*) relates to the specific characteristics of the selection process. In fact, the majority of evaluators appointed to select meritorious applications come from the academic domain and are often leading authorities in their field (Bronzini and Piselli, 2016).[11] Based on the notion of homophily, which refers to the tendency of entities to associate and bond with similar entities (Lazarsfeld and Merton, 1954; Ruef et al., 2003), academic partners may particularly value the outcome of the evaluation process carried out by reputable people who apply their same judgment criteria. As such, additional information conveyed via the subsidized amount may not be necessary for their collaboration decision.

By contrast, it is less likely that professionals from business domains act as evaluators in competitive subsidy programs due to possible conflicts of interest. Due to the lower (or the lack of) background commonality, corporates may perceive the mere subsidy award information as not informative enough to assess the innovation's market potential, requiring the additional and richer information on the potential partner conveyed by *activating signals*. Not only is the subsidy amount closely aligned to commercial goals, but it is also more indicative of the firm's ability to reach them. Additionally, as the subsidized amount increases, so does the attention that corporate receivers pay to it. In sum, compared to *pointing signals*, *activating signals* are more able to reduce the higher level of uncertainty perceived by corporates that typically operate in more volatile contexts and face larger bankruptcy risks (than their academic counterparts).[12]

[10] Under IFRS (International Financial Reporting Standards) and GAAP (Generally Accepted Accounting Principles) (FRS 101) accounting standards, R &D tax credits fall within the scope of investment tax credits (ITCs). As ITCs are typically government incentive schemes assigned through the tax system, entities should account for them using IAS (International Accounting Standards) 20 *Government Grants*, as they do with other forms, for instance, selective subsidies (Deloitte, 2017; https://www2.deloitte.com/content/dam/Deloitte/us/Documents/audit/us-audit-interpretive-guidance-on-contingencies.pdf). "Under IFRS, the R&D credit is, in substance, a government grant towards R&D expenditure" (KPMG, 2016; https://assets.kpmg/content/dam/kpmg/ie/pdf/2016/08/ie-guidance-note-accounting-for-rd-tax-credits.pdf).

[11] Bronzini and Piselli (2016), for instance, state that the appointed evaluators were independent of the regional government and were chosen from among professionals accredited by the Italian Ministry of Education, Universities and Research. Islam et al. (2018) indicate that the majority of reviewers in the assessment team of the 2009 Advanced Research Projects Agency-Energy grant program were drawn from the academic domain. Additionally, a non-systematic web search of the composition of committees in major selective programs across EU countries suggests that this practice is common.

[12] Worth noting is that academic partners, being more likely than corporates to collaborate with firms whose projects are "far from the market", may bear a higher risk than corporates. However, the resources dedicated to pre-competitive collaboration are likely to be lower than those allocated to a collaborative project close to the market. Further, in the case of public universities, it is very unlikely for the State to make them fail.

4. Data

4.1. Innovation policy schemes: the case of Spain

Spain is the context of our analysis. Public subsidies are particularly important in this country due to the relative underdevelopment of the VC market (compared to, for instance, the US), which shows levels of inefficiency comparable to those of other Southern European countries (e.g., Martin et al., 2002; Pintado et al., 2007). In this study, we focus on both selective subsidy programs administered by the central government and local administrations, and automatic procedures that Spanish firms accessed during the observation period 2001–2007.

In Spain, a substantial amount of R&D expenses leverages public support. Huergo and Moreno (2017) point out that 20% of business R&D expenditure is financed by government initiatives. Over our observation period, the Spanish government implemented two different national plans: the R&D National Plan 2000–2003 (Plan Nacional de I + D+I 2000–2003) and the R&D National Plan 2004–2007 (Plan Nacional de I + D+I 2004–2007). Both plans aimed to introduce fiscal and regulatory measures to incentivize private R&D activities. The ultimate objective was twofold: to create a favorable environment for boosting innovation and social welfare, and to contribute to the competitiveness of local firms.

Over the period 2001–2007, the two similar R&D National Plans offered support for different types of projects:[13] i) promotion of skilled human resources through training, mobility, and hiring; ii) R&D projects related to both basic and applied science and technology; iii) support to the implementation and exploitation of new innovations and technologies; iv) adoption of high-tech equipment; v) special projects devoted mainly to the participation of Spanish innovative institutions in international cooperation programs, dissemination of scientific knowledge, and international transfer of technologies. All these types of projects were financed by subsidies in the form of grants or loans, and mostly channeled through the Centre for the Development for Industrial Technology (CDTI). In addition to these forms of subsidy schemes, the two R&D National Plans also included R&D tax credits, where tax deductions were calculated based on the volume of expenses and their increase. R&D expenses broadly include an array of innovation-related costs ranging from wages, scientific instruments, quality certificates, licenses and patents, to engineering services and industrial design.

As Busom et al. (2014) noted, the public R&D subsidy system in Spain is designed so that the amount of direct support is at least double the amount of tax credits. However, to access competitive subsidies, firms have to submit formal applications to the government agency, which selects projects characterized by technical and economic feasibility as well as considerable market potential. As to the R&D tax credits, the eligible costs are identified by the tax authority, and over the last three decades, the proportion of deductible R&D expenses reached 50% (Huergo and Moreno, 2017).

4.2. Sample

The empirical analysis of this study uses data from the Encuesta sobre Estrategias Empresariales (ESEE), which is an annual survey of a representative sample of Spanish manufacturing firms conducted by the SEPI Foundation and the Spanish Ministry of Industry. Extensive innovation-related research on the Spanish economy draws on this large-scale dataset (e.g., Doraszelski and Jaumandreu, 2013; González and Pazó, 2008; González et al., 2005; Guadalupe et al., 2012).[14] By including both low- and high-tech industries as well as SMEs and large companies, this representative dataset differs from the datasets used in most prior studies on subsidies and collaborations, which typically focus on new technology-based firms in emergent, R&D-intensive sectors (Colombo et al., 2006; Grilli and Murtinu, 2018; Islam et al., 2018). ESEE thus offers a broader and more nuanced picture of the phenomenon at stake. The survey has specific sections featuring detailed information on the firm's financing of innovation projects and collaborative activities, which serve to build the main variables in our model specification. In particular, the key advantage of this database is the possibility to measure the monetary amount of R&D subsidies. This information allows investigating the dual nature of subsidy-enabled signals and their different salience for different partner types. The survey respondents are CEOs, and data were gathered using direct interviews supported by a questionnaire.

Our dataset encompasses the period 2001–2007 and potentially consisted of 31,200 firm-year observations. However, many observations had missing values even in basic information.[15] After their elimination, we arrived at a final sample of 2426 firm-year observations. This sample size is comparable to previous studies that use ESEE data (e.g., Arqué-Castells and Mohnen, 2015; Busom et al., 2017; Huergo, 2006; Mate-Garcia and Rodríguez-Fernández, 2008). To reassure the reader of the representativeness of our sample compared to the ESEE population of Spanish firms, we conducted two representativeness tests, which showed that there are no statistically significant differences between the ESEE population and the final sample in terms of industry composition (p-value = 0.84) and the distribution of firm size (p-value = 0.94). As regards the latter test, we used four dummy variables for different size intervals: *Micro*, *Small*, *Medium*, and *Large* equal to one if the firm has fewer than ten employees, ten to 49 employees, 50 to 249 employees, and 250 or more employees, respectively.

As some firms stopped answering the survey during the sample period for multiple reasons (e.g., mergers and changes to non-industrial activities), our panel sample is unbalanced.[16] The sample firms represent 20 industrial sectors according to the NACE-Rev.1 classification (National Classification of Economic Activities). The textile, food and tobacco, chemicals and metal products sectors are the most represented industries, reflecting the actual distribution of Spanish manufacturing firms. In Table 2, we show the distribution of firms engaged in collaborations with other firms only, with universities only, or with both, conditional to both the subsidy participation status and firm size. In terms of distribution of the subsidy programs, in our sample, the proportion of firms awarded a selective subsidy is around 15%. This figure is in line with the recent study of Huergo and Moreno (2017) using data sourced from the CDTI database and a database provided by the Spanish National Institute of Statistics in the period 2002–2005. The proportion of firms awarded an automatic subsidy is around 16%.

5. Method

5.1. Estimation

To estimate the influence of a subsidy award and the amount

[13] The information on the R&D National Plan 2000-2003 and the R&D National Plan 2004-2007 was collected from: http://www.idi.mineco.gob.es/stfls/MICINN/Investigacion/CIENCIA/FICHERO/pnidiresumen.pdf and http://www.idi.mineco.gob.es/stfls/MICINN/Investigacion/FICHEROS/Plan_Nacional_Vol_IDoc.pdf. For other recent academic research on R&D public support in Spain, please refer to Blanes and Busom (2004), Busom and Fernandez-Ribas (2008), Busom et al. (2014), and Huergo and Moreno (2017).

[14] For a comprehensive list of works, see https://www.fundacionsepi.es/investigacion/esee/en/sesee_articulos.asp

[15] For instance, considering the industrial sector, out of 31,200 potentially usable observations, only 12,131 have non-missing values.

[16] We include in our regressions only firms that answered the survey for at least three consecutive years. More generally, unbalanced panel datasets are common to all studies using survey-based data (for more details see, for instance, Eckhardt et al., 2006) and may be driven by survivorship bias (that is, only firms that survived up to the survey date are included in the analysis), and this attrition may bias our results. In Section 6.5.1, we test for the presence of attrition in our data, and we show that our findings remain stable.

Table 2
Distribution of sample firms across collaboration and subsidy types.

		Collaboration type			
		Corporate only	Academic only	Both	No collaboration
Selective R&D subsidy only	SME	11	6	20	6
	Large	5	4	32	7
Automatic R&D subsidy only	SME	20	4	18	13
	Large	19	5	31	7
Both	SME	12	7	18	4
	Large	4	5	50	3
No R&D subsidy	SME	61	50	38	606
	Large	31	33	39	87

SMEs are defined as those firms whose number of employees is lower than 250 (in line with the European Union definition of SMEs). Numbers refer to the number of firms.

awarded on the firm's likelihood of collaborating with academic or corporate partners, we initially estimated a bivariate probit model where the two dependent variables are *Corporate collaboration* and *Academic collaboration*. The model consists of two pooled probit equations estimated simultaneously to control for the potential covariance between the two error terms (a firm's attempt to establish a collaboration with a corporate partner may not be independent of the attempt to establish a collaboration with an academic partner, and vice versa). In other words, the model safely assumes that the corporate market for collaborations may not be independent of the academic market. Standard errors are clustered at the firm-level.

5.2. Variables and measures

5.2.1. Dependent variable

The dependent variables of this study are *Corporate collaboration* and *Academic collaboration*. *Corporate collaboration* (*Academic collaboration*) is a dummy that equals one if firm i established a collaboration with a (n) corporate (academic) partner at time t.

5.2.2. Independent variables

Our independent variables are: (i) four dummy variables that equal one if firm i was awarded a selective R&D subsidy at time *t-1* and *t-2*, respectively (*Selective R&D subsidy (t-1)* and *Selective R&D subsidy (t-2)*), an automatic R&D subsidy at time *t-1* and *t-2*, respectively (*Automatic R&D subsidy (t-1)* and *Automatic R&D subsidy (t-2)*); and (ii) the logarithms of the total amount raised through R&D subsidies by firm i at time *t-1* and *t-2*, respectively (*Total subsidized R&D amount (t-1)* and *Total subsidized R&D amount (t-2)*.[17] Worth noting is that the arguments of the logarithms of all independent and control variables are augmented by one.

5.2.3. Control variables

We control for a large number of factors potentially influencing the relationship between subsidies and collaborations. First, we control for the firm's previous experience in collaborating with corporate and/or academic partners. *Past collaboration experience* is a dummy that equals one if firm i at time t established collaborations with corporate or academic partners in previous years. Second, we control for the logarithmic age of the firm (*Age*) at time t, and for the logarithmic number of employees (*Size (t-1)*) at time *t-1*. Third, we add innovation-related variables at time *t-1* to our model specification: *R&D intensity (t-1)* is the ratio between the logarithm of total (internal and external) R&D expenses and the logarithm of sales value; *Patents (t-1)* is the logarithmic number of patents; and *EU project (t-1)* is a dummy that equals one if firm i joined a European research project. Fourth, we control for the human capital within the firm, measured by a dummy that equals one in the presence of personnel with corporate R&D experience (*Human capital (t-1)*). Fifth, we control for the debt exposure of firm i at time *t-1*: *Debt/Equity (t-1)* is the leverage, and *Debt/Sales (t-1)* is the debt-to-sales ratio. Sixth, we include the operating performance of firm i at time *t-1* calculated as the return-on-assets ratio (*ROA (t-1)*). Seventh, we control for other firm-specific variables at time *t-1*: *Listed (t-1)* is a dummy that equals one if firm i is listed; *Group (t-1)* is a dummy that equals one if firm i belongs to a business group; *Foreign controlled (t-1)* is a dummy that equals one if firm i's equity owned by foreign shareholders exceeds 50%; *Family (t-1)* is a dummy that equals one if firm i belongs to a family business group; and *Limited liability (t-1)* is a dummy that equals one if the legal form of firm i is classified as limited liability. Eighth, we control for the level of competition faced by firm i measured by the C3 concentration index (*Competition (t-1)*): the sum of the market shares of the first three competitors in firm i's relevant market.[18] Finally, we include year and industry dummies.

6. Results

6.1. Descriptive statistics

In Table 3, we report the descriptive statistics of the dependent, independent, and control variables. The data suggest that firms included in the sample are more likely to establish collaborations with academic partners (22.1%) than with corporate peers (8.98%). In addition, slightly over 7% of the sample shows past experience with collaborations, while participation in EU projects is quite rare, as is being publicly listed. In terms of human capital, only around 5% of the sample has people with corporate R&D experience, while almost 35% (5%) is part of a (family) business group.

No serious issues of multicollinearity seem to exist in our data, and the Variance Inflation Factor (VIF) tests reassure us: the mean VIF is 2.31, which is significantly below the commonly adopted threshold of 10 (O'Brien, 2007).

6.2. Main results

Table 4 reports the estimated coefficients of the baseline bivariate probit models, where in columns (1), (3), and (5) the dependent variable is *Corporate collaboration*, while in columns (2), (4), and (6) the dependent variable is *Academic collaboration*. In columns (1)–(2), estimations refer to the full sample; we then split the full sample between SMEs (columns (3)–(4)), i.e., firms with fewer than 250 employees (in line with the European Union definition of SMEs) – and large firms (columns (5)–(6)), i.e., firms with 250 or more employees.

Firm size is a relevant attribute of the signaler that may affect the effectiveness of the signaling process on different receivers (Collins et al., 1987; Fagiolo and Luzzi, 2006; Slovin et al., 1992). We expect a stronger influence of both *pointing* and *activating signals* for SMEs across receiver types. Indeed, the lower legitimacy of SMEs and the larger

[17] As explained in Section 3, the total amount raised includes financial resources from both selective and automatic subsidies. To note is that the amount associated with automatic subsidies (such as R&D tax credits) is typically given *ex-post* (i.e., after R&D expenditure). However, such amount (summed up to the amount awarded through selective subsidies) may exert a signaling role in our model specification. As such, we use lagged variables at time *t-1* and *t-2*; that is, by construction, the total amount raised through selective and automatic subsidies materializes before the collaboration formation. Furthermore, certain selective subsidies (e.g., regional incentives in Spain) are paid *a posteriori*, after the relative activities have been justified. In section 6.5.1, we re-estimate our main results by separating the amount awarded through selective subsidies from the amount awarded through automatic subsidies.

[18] We also used alternative measures, such as the C4 concentration index, the market share of the main competitor, and a measure of customer concentration. Results are in line with those shown in Table 4.

Table 3
Descriptive statistics.

Variable	Mean	Median	S.D.	Min	Max
Corporate collaboration	0.0898	0	0.2859	0	1
Academic collaboration	0.2210	0	0.4150	0	1
Selective R&D subsidy	0.0391	0	0.1938	0	1
Automatic R&D subsidy	0.0487	0	0.2152	0	1
Total subsidized R&D amount	0.8806	0	2.0748	0	11.6799
Past collaboration experience	0.0734	0	0.2607	0	1
Age	3.0227	3.0445	0.7818	0.6931	5.1533
Size	4.3191	3.9703	1.4761	1.9460	9.5764
R&D intensity	0.2524	0	0.3431	0	1.2552
Patents	0.0925	0	0.4244	0	5.4553
EU project	0.0118	0	0.1078	0	1
Human capital	0.0534	0	0.2249	0	1
Debt/Equity	1.6284	0.7302	10.3305	0.0201	827.8013
Debt/Sales	0.3861	0.2678	0.5631	0.0065	25.9509
ROA	0.2125	0.1137	1.2035	−0.4694	115.1403
Listed	0.0213	0	0.1444	0	1
Group	0.3497	0	0.4769	0	1
Foreign controlled	0.0595	0	0.2365	0	1
Family	0.0475	0	0.2128	0	1
Limited liability	0.2213	0	0.4151	0	1
Competition	23.5958	14	26.6034	0	100

information gap on their future prospects and innovation potential (Meuleman and De Maeseneire, 2012) magnifies the benefit that can be achieved from signaling the firm's quality to would-be partners by attracting their attention and lowering the uncertainty surrounding the firm's innovation (Feldman and Kelley, 2006). The strength of both signals is likely to be higher for SMEs, also due to higher opportunity costs when applying for subsidies (Grilli and Murtinu, 2018): diverting employees' efforts from core activities to onerous application processes is a rational strategy if, and only if, the proponent has a high quality project and/or eligible R&D expenses, and hence a good chance of obtaining the subsidy (Islam et al., 2018). In sum, the two signals should help legitimize SMEs as innovative players, and enhance the trust of third parties (Kleer, 2010).

It seems that in the full sample (column (1)), what matters for collaboration with corporate partners is the total amount raised through subsidies: the coefficient of *Total subsidized R&D amount (t-2)* is positive and statistically significant at the 10% confidence level. Starting from the baseline probability of establishing a corporate collaboration (i.e., 8.98% - see Table 3), the estimated semi-elasticity (i.e., δ*Corporate collaboration*/δln(*Total subsidized R&D amount (t-2)*)) at the median value of the subsidized amount for the firms awarded a subsidy (i.e., around €172,000) is +5.2%. Estimating the semi-elasticity at the 75° and 90° percentiles of the same distribution of values (i.e., around €529,000 and €1,540,000), such semi-elasticity in establishing a corporate collaboration at time *t* is +6.7% and +8.2%, respectively.

When splitting the sample between SMEs (column (3)) and large firms (column (5)), the positive association between the amount raised through subsidies and *Corporate collaboration* holds (at the 5% confidence level) only for SMEs. In the subsample of SMEs, considering that the baseline probability of establishing a corporate collaboration for SMEs is 14.26%, the estimated semi-elasticity at the median value of the subsidized amount for SMEs awarded a subsidy (i.e., around €85,000) is +10%. As above, at the values corresponding to the 75° and 90° percentiles of the distribution (i.e., around €249,000 and €561,000), the estimated semi-elasticities are +14% and +17.4%, respectively.

Surprisingly, the coefficient of *Selective R&D subsidy (t-2)* is negative (significant at 10%) for both large firms and SMEs. A possible interpretation might be that the award of a selective subsidy, acting as a certification of the quality of the firm's innovation, might lower the firm's willingness to collaborate with external corporate partners and instead persuade it to pursue a go-it-alone strategy in order to capture the entire economic value created by the innovation. It might also be that these firms exploit the award of a selective subsidy as a *pointing signal* toward academic institutions (see below) and/or other market players (e.g., banks, government agencies) in order to, for instance, raise additional funds and/or internationalize operations.

Turning to the association between the award of a selective subsidy and the likelihood of establishing an academic collaboration, this is positive and statistically significant in the full sample (column (2)) (at times *t-1* and *t-2*), as well as in the two subsamples (at time *t-1* for large firms and at *t-2* for SMEs). A possible explanation as to why large firms might be quicker at exploiting the *pointing signal* than SMEs is that large firms are likely to have (and send) more signals and of different types (e.g., patents, being more diversified), and frequent and repetitive signaling can accelerate the effectiveness of the signaling process (Janney and Folta, 2003; Balboa and Martí, 2007). Also, the higher legitimacy, visibility, and resource endowments of large firms might help expedite the effects of the signal. In the full sample, assuming that the marginal effects at time *t-1* and *t-2* can be summed up, the associated marginal effect is +10.6%; thus, the likelihood of establishing a collaboration with an academic partner moves from 22.1% (see Table 3) to 32.7%. When splitting the sample between SMEs (column (4)) and large firms (column (6)), the marginal effect associated with *Selective R&D subsidy* is +5.4% (at time *t-2*) and +4.4% (at time *t-1*) for SMEs and large firms, respectively. However, the marginal effect for large firms is not statistically significant. When considering the point estimates of marginal effects, the baseline probability of establishing an academic collaboration for SMEs (large firms) is equal to 12.48% (52.37%). Thus, the likelihood of establishing an academic collaboration with respect to the baseline probability moves from 12.48% to 17.9% (i.e., an increase of almost +43.5%) for SMEs, and from 52.37% to 56.8% (i.e., an increase of + 8.4%) for large firms. Therefore, the association between a selective subsidy award and the likelihood of establishing an academic collaboration is stronger for SMEs.

Worth noting is that the mere award of automatic subsidies is not significantly associated with the likelihood of establishing a collaboration with any partner type. According to these results, automatic subsidies do not act as *pointing signals*.

As regards the control variables, our results seem to show a positive and significant association between the firm's past experience in collaborations and the likelihood of establishing current collaborations (regardless of type). Three other notable findings relate to a positive association between: i) firm size and likelihood of establishing academic collaborations (especially for SMEs); ii) R&D intensity and likelihood of forming both types of collaborations (with the exception of academic collaborations in the subsample of large firms); and iii) the presence of personnel with corporate R&D experience and the likelihood of forming both types of collaborations (with the exception of corporate collaborations in the subsample of SMEs). Finally, belonging to a family business group positively affects the likelihood of establishing collaborations with corporate partners for large firms.

6.3. Inter-temporal patterns in collaborations

While controlling for the firm's previous experience in collaborating with third parties, our estimates in Table 4 may not properly take into account the intertemporal patterns of the different types of collaborations, and how these patterns may be correlated with the award of a subsidy and/or the total amount raised through the subsidy. Building on Belderbos et al. (2015), in Table 5 we extend the model specification in Table 4 with the three dummy variables suggested by these authors so as to capture the recent, persistent, and discontinued nature of collaborations, interacted with the two types of collaboration partners (i.e., corporate and academic). Specifically, *Recent corporate* is a dummy that equals one if the focal firm has an active corporate collaboration at time *t-1* but not at time *t-2*; *Persistent corporate* is a dummy that equals

Table 4
Baseline results.

	(1) Corporate collaboration All firms	(2) Academic collaboration All firms	(3) Corporate collaboration SMEs	(4) Academic collaboration SMEs	(5) Corporate collaboration Large firms	(6) Academic collaboration Large firms
Selective R&D subsidy (t-1)	−0.2848	0.3446*	−0.3653	0.0567	−0.0093	0.4420*
	(0.2364)	(0.1887)	(0.2875)	(0.2821)	(0.3702)	(0.2430)
Selective R&D subsidy (t-2)	−0.2534	0.5112***	−0.3877*	0.5138**	−0.4453*	0.4068
	(0.1758)	(0.1711)	(0.2175)	(0.2561)	(0.2519)	(0.2507)
Automatic R&D subsidy (t-1)	0.1526	−0.1575	0.2853	−0.2278	0.0784	−0.0606
	(0.2054)	(0.2014)	(0.3047)	(0.3142)	(0.3781)	(0.2838)
Automatic R&D subsidy (t-2)	−0.0036	−0.0129	−0.1177	0.2031	0.0377	−0.3881
	(0.1891)	(0.1896)	(0.2722)	(0.2787)	(0.3001)	(0.2722)
Total subsidized R&D amount (t-1)	0.0592	−0.0324	−0.0041	−0.0163	0.1096	0.0133
	(0.0556)	(0.0454)	(0.0767)	(0.0723)	(0.0881)	(0.0596)
Total subsidized R&D amount (t-2)	0.0795*	−0.0127	0.1543**	−0.0286	0.0727	0.0381
	(0.0447)	(0.0408)	(0.0668)	(0.0639)	(0.0588)	(0.0571)
Past collaboration experience	1.2094***	1.5384***	1.2634***	1.5911***	1.2537***	1.6513***
	(0.1442)	(0.1382)	(0.1836)	(0.1857)	(0.2207)	(0.2280)
Age	−0.1220	0.0726	0.0068	0.1282	−0.5207***	0.0050
	(0.0881)	(0.0920)	(0.1136)	(0.1191)	(0.1492)	(0.1396)
Size (t-1)	0.0704	0.1965***	0.0412	0.2981***	0.1943	0.0298
	(0.0593)	(0.0631)	(0.0962)	(0.1079)	(0.1351)	(0.1600)
R&D intensity (t-1)	2.4958***	0.4487**	2.6959***	0.6727**	1.8773***	−0.2649
	(0.2065)	(0.2158)	(0.2474)	(0.2778)	(0.3694)	(0.3440)
Patents (t-1)	−0.1575*	0.1474	0.0017	0.0210	−0.1864	0.2218
	(0.0945)	(0.0919)	(0.1496)	(0.1114)	(0.1174)	(0.1416)
EU project dummy (t-1)	−0.3549	0.1918	−0.4801	0.2558	0.1174	0.2229
	(0.3771)	(0.4112)	(0.5179)	(0.5726)	(0.6327)	(0.5987)
Human capital (t-1)	0.4393*	0.5615***	0.5741	0.6334**	0.3722*	0.5394*
	(0.2558)	(0.1961)	(0.4655)	(0.2795)	(0.2143)	(0.2770)
Debt/Equity (t-1)	−0.0046	−0.0115	−0.0278	−0.0062	0.0420	−0.0494
	(0.0125)	(0.0172)	(0.0329)	(0.0107)	(0.0585)	(0.0701)
Debt/Sales (t-1)	−0.2413*	−0.0210	−0.1715	−0.0199	−0.1874	−0.1081
	(0.1394)	(0.0522)	(0.1789)	(0.0419)	(0.2652)	(0.2660)
ROA (t-1)	0.0237	0.0076	0.0117	0.0578	0.4529	0.1453
	(0.0985)	(0.0461)	(0.0098)	(0.2727)	(0.3979)	(0.3499)
Listed (t-1)	0.7682***	0.0576	−0.2559	−7.8324***	0.8782**	0.6708**
	(0.2859)	(0.2725)	(0.3382)	(0.4330)	(0.3666)	(0.3227)
Group (t-1)	−0.1685	0.1253	−0.0482	0.0204	−0.3770	0.1982
	(0.1426)	(0.1437)	(0.1810)	(0.1836)	(0.2313)	(0.2095)
Foreign controlled (t-1)	0.0792	−0.1893	0.0978	−0.1005	0.0642	−0.3097
	(0.1657)	(0.1456)	(0.2491)	(0.2063)	(0.2034)	(0.2001)
Family (t-1)	0.3222**	0.0452	0.0432	0.0120	1.2030***	0.0056
	(0.1456)	(0.1455)	(0.1849)	(0.1756)	(0.3002)	(0.3015)
Limited liability (t-1)	−0.0698	−0.1454	−0.0167	−0.1821	−0.1535	−0.4132
	(0.1282)	(0.1345)	(0.1596)	(0.1727)	(0.2307)	(0.2660)
Competition (t-1)	0.0003	−0.0018	−0.0022	−0.0017	0.0009	−0.0061
	(0.0021)	(0.0023)	(0.0026)	(0.0029)	(0.0044)	(0.0039)
Year dummies	Y	Y	Y	Y	Y	Y
Industry dummies	Y	Y	Y	Y	Y	Y
Obs.	2426		1832		594	

Regressions estimated with an intercept term. Standard errors in brackets.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

one if the focal firm has an active corporate collaboration both at time *t-1* and at time *t-2*; *Discontinued corporate* is a dummy that equals one if the focal firm has an active corporate collaboration at time *t-2* but not at time *t-1*; *Recent academic* is a dummy that equals one if the focal firm has an active academic collaboration at time *t-1* but not at time *t-2*; *Persistent academic* is a dummy that equals one if the focal firm has an active academic collaboration both at time *t-1* and at time *t-2*; *Discontinued academic* is a dummy that equals one if the focal firm has an active academic collaboration at time *t-2* but not at time *t-1*.

Interestingly, the results in Table 5 confirm the positive association between the amount raised through subsidies (at time t-2) and the likelihood of forming corporate collaborations for SMEs (column (3)): despite that the coefficient of *Total subsidized R&D amount (t-2)* is only close to significance (p = 0.12), the average marginal effect is statistically significant at the 10% confidence level (p = 0.06). The estimated semi-elasticities at the 75° and 90° percentiles of the distribution of the subsidized amount for SMEs awarded a subsidy are +9% and +10.9%, respectively. These effects are still sizeable, although smaller than those in Table 4, showing that our finding of a positive *activating signal* of a subsidized R&D amount for SMEs still holds after controlling for an important determinant such as intertemporal patterns in collaborations. As in Table 4, the coefficient of *Selective R&D subsidy (t-2)* is negative (significant at 5%) for large firms; by contrast, such negative coefficient vanishes in the sample of SMEs. This finding for large firms is consistent with the negative and statistically significant coefficient of firm age: large older firms are likely endowed with more resources, hence their lesser need for corporate collaborations.

Table 5
Inter-temporal patterns in the type of technological collaborations.

	(1) Corporate collaboration All firms	(2) Academic collaboration All firms	(3) Corporate collaboration SMEs	(4) Academic collaboration SMEs	(5) Corporate collaboration Large firms	(6) Academic collaboration Large firms
Selective R&D subsidy (t-1)	−0.2360	0.3548*	−0.4020	0.1691	0.1754	0.5192**
	(0.2434)	(0.2031)	(0.3049)	(0.3128)	(0.3594)	(0.2611)
Selective R&D subsidy (t-2)	−0.1967	0.5767***	−0.3042	0.5517*	−0.5447**	0.4723*
	(0.1689)	(0.1795)	(0.2270)	(0.3029)	(0.2518)	(0.2594)
Automatic R&D subsidy (t-1)	0.2512	−0.1465	0.3600	−0.2910	0.2019	0.0778
	(0.2225)	(0.2114)	(0.3173)	(0.3144)	(0.4012)	(0.2991)
Automatic R&D subsidy (t-2)	−0.0400	0.0614	−0.2242	0.4236	0.0560	−0.3616
	(0.1993)	(0.2005)	(0.2796)	(0.3024)	(0.3151)	(0.2978)
Total subsidized R&D amount (t-1)	0.0582	−0.0444	0.0051	−0.0374	0.1049	−0.0379
	(0.0603)	(0.0471)	(0.0837)	(0.0708)	(0.0944)	(0.0639)
Total subsidized R&D amount (t-2)	0.0356	−0.0547	0.1079	−0.0706	0.0455	0.0219
	(0.0473)	(0.0433)	(0.0699)	(0.0710)	(0.0599)	(0.0626)
Past collaboration experience	0.9474***	1.1826***	0.9829***	0.9872***	1.0469***	1.6793***
	(0.1400)	(0.1466)	(0.1776)	(0.1984)	(0.2120)	(0.2407)
Recent corporate	0.7917***		0.8772***		0.5317	
	(0.1901)		(0.2326)		(0.3547)	
Persistent corporate	1.0163***		1.1991***		0.8317***	
	(0.1488)		(0.2005)		(0.2348)	
Discontinued corporate	−0.4362**		−0.0818		−0.7603***	
	(0.2102)		(0.3418)		(0.2894)	
Recent academic		0.7815***		1.1058***		0.1253
		(0.1966)		(0.2598)		(0.3154)
Persistent academic		1.0240***		1.5191***		0.5043**
		(0.1656)		(0.2155)		(0.2168)
Discontinued academic		−0.4283**		0.1891		−0.8870***
		(0.2070)		(0.3260)		(0.2625)
Age	−0.1157	0.0987	−0.0171	0.1425	−0.5001***	0.0847
	(0.0866)	(0.0866)	(0.1183)	(0.1064)	(0.1458)	(0.1459)
Size (t-1)	0.0558	0.1674***	0.0262	0.2189**	0.1804	0.0344
	(0.0562)	(0.0577)	(0.0959)	(0.0945)	(0.1261)	(0.1552)
R&D intensity (t-1)	2.0942***	0.4349**	2.2986***	0.5883**	1.4949***	−0.1818
	(0.1820)	(0.1940)	(0.2139)	(0.2427)	(0.3700)	(0.3421)
Patents (t-1)	−0.1115	0.1204	0.0963	0.0466	−0.1840	0.1774
	(0.0886)	(0.0926)	(0.1411)	(0.1200)	(0.1136)	(0.1488)
EU project dummy (t-1)	−0.0849	0.0559	−0.3065	−0.2727	0.3336	0.0514
	(0.3611)	(0.3798)	(0.4646)	(0.5960)	(0.6309)	(0.5206)
Human capital (t-1)	0.4190*	0.5262***	0.4508	0.5815**	0.4237*	0.5857*
	(0.2232)	(0.1952)	(0.3982)	(0.2655)	(0.2196)	(0.3037)
Debt/Equity (t-1)	−0.0059	−0.0103	−0.0293	−0.0077	0.0442	−0.0295
	(0.0122)	(0.0151)	(0.0305)	(0.0102)	(0.0590)	(0.0660)
Debt/Sales (t-1)	−0.1469	0.0009	−0.0828	−0.0078	−0.1385	−0.1274
	(0.1098)	(0.0390)	(0.0715)	(0.0380)	(0.2556)	(0.2425)
ROA (t-1)	0.0212	0.0531	0.0145	0.0578	0.6825	0.3290
	(0.0261)	(0.2309)	(0.0094)	(0.2523)	(0.4721)	(0.4433)
Listed (t-1)	0.7537***	0.1033	−0.6473	−7.1807***	0.9187***	0.6668**
	(0.2714)	(0.2647)	(0.3938)	(0.4994)	(0.3479)	(0.3327)
Group (t-1)	−0.1204	0.2121	−0.0317	0.1282	−0.3116	0.3299
	(0.1380)	(0.1384)	(0.1744)	(0.1802)	(0.2313)	(0.2178)
Foreign controlled (t-1)	0.0434	−0.1390	0.1292	0.1408	−0.0549	−0.3647*
	(0.1583)	(0.1427)	(0.2219)	(0.1964)	(0.1978)	(0.2062)
Family (t-1)	0.3441**	0.1049	0.0960	0.1105	1.2103***	0.1164
	(0.1518)	(0.1525)	(0.1973)	(0.1843)	(0.3173)	(0.3278)
Limited liability (t-1)	−0.0531	−0.1199	0.0098	−0.1964	−0.1391	−0.3779
	(0.1257)	(0.1226)	(0.1587)	(0.1496)	(0.2259)	(0.2565)
Competition (t-1)	0.0003	−0.0017	−0.0027	−0.0017	0.0016	−0.0059
	(0.0021)	(0.0022)	(0.0024)	(0.0027)	(0.0045)	(0.0040)
Year dummies	Y	Y	Y	Y	Y	Y
Industry dummies	Y	Y	Y	Y	Y	Y
Obs.	2426		1832		594	

Regressions estimated with an intercept term. Standard errors in brackets.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

As regards the award of a selective subsidy, its association with the likelihood of establishing an academic collaboration confirms the evidence in Table 4: the only difference is that for large firms, the coefficient of *Selective R&D subsidy (t-2)* is also statistically significant at the 10% confidence level. In the case of SMEs (column (4)), the marginal effect of *Selective R&D subsidy (t-2)* is +4.8%. As regards large firms, assuming that the marginal effects at time *t-1* and *t-2* can be summed up, the associated marginal effect is +12.8% (but not statistically significant). Even if the point estimate of marginal effects is higher for larger firms, the association between the award of a selective subsidy and the likelihood of establishing an academic collaboration is stronger for SMEs. Indeed, while for SMEs the likelihood of establishing an academic collaboration with respect to the baseline probability moves from 12.48% to 16.9% (i.e., an increase of +35.42%), for large firms this baseline probability moves from 52.37% to 65.17% (i.e., an increase of +24.44%). Again, no significant association is found between the mere award of an automatic subsidy and the likelihood of establishing a technological collaboration.

With respect to the nature of collaborations, the marginal effects associated with the coefficients in Table 5 indicate that in the subsample of SMEs, recent (persistent) collaborations with firms increase the likelihood of forming corporate collaborations by 6.4% (8.7%), while the marginal effect for recent (persistent) academic collaborations is equal to +8.1% (+11.1%). All marginal effects are statistically significant at the 1% confidence level. Interestingly, in the subsample of large firms, only persistent past collaborations with firms positively and significantly (at the 5% confidence level) influence the likelihood of forming a corporate collaboration: the estimated marginal effect is equal to +6.5%. Further, for large firms, discontinued past collaborations with firms negatively influence (at the 10% confidence level) the likelihood of forming corporate collaborations. Thus, it seems that large firms without continuous involvement with corporates in the past are less likely to collaborate with them in the future.

As regards the control variables, notable findings relate (as in Table 4) to a positive association between: i) R&D intensity and the likelihood of forming both types of collaborations (with the exception of academic collaborations in the subsample of large firms); and ii) the presence of personnel with corporate R&D experience and the likelihood of forming both types of collaborations (with the exception of corporate collaborations in the subsample of SMEs). As in Table 4, belonging to a family business group positively affects the likelihood of large firms establishing collaborations with corporate partners.

6.4. Selection bias

Our main results in Table 4 may be (at least partially) driven by the presence of R&D inactive firms, that is, firms that do not show any R&D expense in the observed timeframe. Since R&D inactive firms are less likely to form collaborations, and subsidy-related variables are negatively correlated (by definition) with the R&D inactive status, our results may be upwardly biased.[19] Thus, we test the potential influence of selection bias by means of the variable addition test of Wooldridge (1995) and Semykina and Wooldridge (2010, 2013).

This test consists in estimating our main model specification in Table 4 augmented with a time-varying inverse Mills ratio (*IMR*) term (for a similar procedure, see, for instance, Croce et al., 2013; Grilli and Murtinu, 2015). To compute *IMR*, we ran a panel probit model where the dependent variable is a dummy variable that equals zero if the firm is R&D inactive, and as an additional regressor, we inserted a dummy variable that equals one if the firm actively applied for R&D tax credits.[20] The purpose of the inclusion of this additional regressor is to avoid a collinearity problem when *IMR* is inserted in the main equation. In other words, the lack of an additional regressor in the nonlinear equation on R&D inactive status implies that *IMR* is calculated starting from the same variables as those included in the main equation. Thus, the coefficient of *IMR* (and those of the other independent variables) may not be statistically significant due to insufficient identifying variation from non-linearities in the panel probit equation on the R&D inactive status. Intuitively, the additional regressor serves as an exclusion restriction for the estimation of the main equation. From a theoretical point of view, the firm's active search for R&D tax credits may represent a strong predictor of the firm's R&D active status. At the same time, this additional regressor is not necessarily linked to access to collaborations. Further, in our main equation, we account for the actual award of R&D tax credits.

In columns (3) and (4) of Table 6, we use a second methodology to test for the potential presence of selection bias in our data: a maximum likelihood Heckman model. In the first stage, we include all sample firms, that is, both R&D active and inactive firms. As above, the dependent variable is still a dummy variable that equals zero if the firm is R&D inactive, and the exclusion restriction is still the dummy variable that equals one if the firm actively applied for R&D tax credits. Finally, in the last two columns of Table 6, we limit our analysis to include R&D active firms only.

Our results in Table 6 are in line with those in Table 4, suggesting that the *pointing signal* emitted by the award of a selective subsidy is positively associated with the formation of academic collaborations only, whereas the *activating signal* emitted by the monetary amount awarded is positively associated with the formation of corporate collaborations only.[21] In columns (1) and (2), the coefficient of *IMR* is not statistically significant, and thus the null hypothesis of the absence of selection bias in our data is not rejected.[22] In columns (3) and (4), at the bottom of Table 6, the coefficient of the exclusion restriction is positive and statistically significant, that is, actively applying for R&D tax credits leads to a more likely R&D active status (first stage estimates are available upon request from the authors).

6.5. Robustness checks

We ran several checks to test the robustness of our main results and to exclude alternative explanations. In the following, we separate the main robustness checks from the other relatively less critical ones.

6.5.1. Main robustness checks

First, the estimation results in Table 4 may inflate the influence of the *activating signal*. Indeed, while the amount raised through subsidies aims at capturing the "partner attraction ability" enabled by the *activating signal*, the associated marginal effect may also include the substantive effect of obtaining financial resources (Colombo et al., 2019). This substantive effect refers to the fact that resources collected through subsidies likely alleviate financing constraints not only in the execution of R&D activities but also in the tasks required to form a collaboration. In fact, such resources allow the firm to invest in new technologies, capital inputs, and materials to incorporate in the innovation processes, and these inputs may ultimately increase innovation efficiency,

[19] Worth noting is that if the goal of the subsidy is to impact the extensive margin rather than the intensive margin, then this is not the case. As such, we keep the R&D inactive firms in our baseline model specifications. However, given that most previous studies show that past R&D performance may (at least partially) explain the likelihood of obtaining a subsidy today, for the sake of prudence, we test for potential selection bias in our data.

[20] We also employed a panel logit model specification and the results hold. To note is that we do not aim to estimate a causal effect of this additional regressor but a correlational relationship that from a statistical point of view allows sufficient variation in the second step to identify the coefficients of interest.

[21] Compared to Table 4, the results for the *activating signal* when controlling for selection bias are also significant at time t-1. Indeed, the coefficient of *Total subsidized R&D amount (t-1)* is statistically significant at the conventional confidence levels in columns (1), (3), and (5). Conversely, compared to Table 4, the results for the *pointing signal* are significant only at time t-2 due to the lack of statistical significance of *Selective R&D subsidy (t-1)* in columns (2), (4), and (6). Furthermore, the negative association between the award of selective subsidies and corporate collaborations is now significant in the full sample at different lags. These findings may be explained by the smaller sample size as compared to Table 4.

[22] Results hold when estimating standard errors in the main equation by means of bootstrap procedures (for more details, see Efron, 1981; Efron and Tibshirani, 1986; Gonçalves and White, 2005).

Table 6
Selection bias.

	Semykina & Wooldridge		Heckman		R&D active firms only	
	(1) Corporate collaboration	(2) Academic collaboration	(3) Corporate collaboration	(4) Academic collaboration	(5) Corporate collaboration	(6) Academic collaboration
Selective R&D subsidy (t-1)	−0.4137*	0.1468	−0.0990*	0.0627	−0.3057	0.1965
	(0.2364)	(0.2023)	(0.0546)	(0.0475)	(0.2286)	(0.1894)
Selective R&D subsidy (t-2)	−0.3048*	0.3625**	−0.0684	0.1013**	−0.3006*	0.3996**
	(0.1818)	(0.1762)	(0.0428)	(0.0442)	(0.1672)	(0.1719)
Automatic R&D subsidy (t-1)	0.0366	−0.2692	0.0338	−0.0270	0.1302	−0.2925
	(0.2167)	(0.2294)	(0.0475)	(0.0465)	(0.1986)	(0.2071)
Automatic R&D subsidy (t-2)	−0.0270	−0.1479	0.0012	−0.0237	−0.0178	−0.0650
	(0.1886)	(0.2084)	(0.0431)	(0.0445)	(0.1786)	(0.1960)
Total subsidized R&D amount (t-1)	0.1289**	0.0200	0.0294**	−0.0053	0.0885*	0.0209
	(0.0568)	(0.0516)	(0.0130)	(0.0110)	(0.0537)	(0.0459)
Total subsidized R&D amount (t-2)	0.0872*	0.0311	0.0190*	0.0034	0.0881**	0.0121
	(0.0447)	(0.0450)	(0.0102)	(0.0093)	(0.0425)	(0.0425)
Past collaboration experience	1.1367***	1.6218***	0.3466***	0.5400***	1.0640***	1.6129***
	(0.1620)	(0.1479)	(0.0515)	(0.0427)	(0.1448)	(0.1392)
Age	−0.2405**	−0.1331	−0.0494*	−0.0212	−0.1474	−0.0379
	(0.1056)	(0.1167)	(0.0254)	(0.0264)	(0.0941)	(0.1027)
Size (t-1)	−0.0161	0.1510*	0.0061	0.0341**	0.0145	0.1273*
	(0.0815)	(0.0884)	(0.0168)	(0.0173)	(0.0621)	(0.0700)
R&D intensity (t-1)	1.4604***	0.3277	0.4898***	0.2497**	1.5800***	0.3886*
	(0.2442)	(0.2614)	(0.1180)	(0.1216)	(0.2077)	(0.2332)
Patents (t-1)	−0.1765*	0.1641	−0.0444*	0.0316	−0.1410	0.1983**
	(0.0951)	(0.1026)	(0.0257)	(0.0218)	(0.0951)	(0.0975)
EU project dummy (t-1)	−0.3189	0.2320	−0.1116	0.0149	−0.2835	0.2884
	(0.3930)	(0.3946)	(0.0730)	(0.0824)	(0.3767)	(0.4095)
Human capital (t-1)	0.4404*	0.4751**	0.0774	0.0842**	0.4672*	0.4577**
	(0.2530)	(0.2075)	(0.0557)	(0.0429)	(0.2532)	(0.1936)
Debt/Equity (t-1)	0.0373	−0.0917*	−0.0026	−0.0012	−0.0061	−0.0200
	(0.0390)	(0.0469)	(0.0039)	(0.0077)	(0.0292)	(0.0473)
Debt/Sales (t-1)	−0.2682	0.0262	−0.0385***	−0.0093	−0.2096	−0.0125
	(0.1887)	(0.0661)	(0.0138)	(0.0132)	(0.1650)	(0.0972)
ROA (t-1)	0.0142	0.7633**	0.0021**	−0.0012	0.0192	0.4344
	(0.0106)	(0.3335)	(0.0010)	(0.0009)	(0.0280)	(0.2864)
Listed (t-1)	0.9249**	0.1340	0.1561**	0.0269	1.0502***	0.3551
	(0.3756)	(0.3551)	(0.0640)	(0.0729)	(0.3712)	(0.3331)
Group (t-1)	−0.3547**	−0.1194	−0.0575	−0.0213	−0.1644	−0.1036
	(0.1544)	(0.1686)	(0.0406)	(0.0411)	(0.1446)	(0.1528)
Foreign controlled (t-1)	0.0419	−0.1847	−0.0000	−0.0407	0.1192	−0.1467
	(0.1680)	(0.1668)	(0.0456)	(0.0403)	(0.1637)	(0.1545)
Family (t-1)	0.3209*	0.2340	0.0715*	0.0291	0.3596**	0.1058
	(0.1767)	(0.1995)	(0.0415)	(0.0411)	(0.1616)	(0.1848)
Limited liability (t-1)	−0.2295	−0.3404*	−0.0620	−0.0605	−0.2272	−0.3461**
	(0.1690)	(0.1788)	(0.0421)	(0.0381)	(0.1465)	(0.1573)
Competition (t-1)	−0.0017	−0.0016	−0.0002	−0.0004	−0.0007	−0.0015
	(0.0027)	(0.0028)	(0.0006)	(0.0006)	(0.0023)	(0.0027)
IMR	0.0608	0.0093				
	(0.0517)	(0.0498)				
Year dummies	Y	Y	Y	Y	Y	Y
Industry dummies	Y	Y	Y	Y	Y	Y
First stage exclusion restriction			0.5700* (0.3147)	0.5952** (0.2760)		
Obs.	1019		1814		1236	

Regressions estimated with an intercept term. Standard errors in brackets.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

proxied, for instance, by the ratio of innovation outputs and innovation inputs (Hirshleifer et al., 2013). Such enhanced innovation efficiency may be the observable trait that truly attracts potential partners. While previous studies distinguish the signaling effect from the substantive effect via implicit assumptions of the characteristics of signalers (e.g., Hsu and Ziedonis, 2013; Stuart et al., 1999), or their type (Pollock et al., 2010), or by means of sophisticated but indirect econometric methodologies (Colombo et al., 2019), we directly account for the two effects by extending our main model specification with two alternative variables of innovation efficiency. Specifically, *Patents/R&D (t-1)*, calculated as the ratio at time *t-1* between the logarithmic number of patents and the logarithm of total (internal and external) R&D expenses, and *Patents/ Total subsidized R&D amount (t-1)*, calculated as the ratio at time *t-1* between the logarithmic number of patents and the logarithm of the total amount raised through R&D subsidies. These variables should capture the deployment of total R&D expenses or financial resources raised through subsidies at time *t-1* and *t-2*, which likely lead to increased innovation efficiency, and thus an observable subsidy-driven substantive effect.[23]

As shown in Table 7 (first four columns), innovation efficiency does not seem to influence the likelihood of collaborating with external partners, and the associated marginal effects are not statistically significant. More importantly, our main results hold.[24]

Second, our results in Table 4 may be affected by two intertwined issues. First, a simultaneity bias might be at play, as some selective programs may require firms to collaborate with third parties ex-ante. In more technical terms, in our baseline empirical specification, the subsidy-related independent variables may potentially be correlated with the error term (via the unobserved collaboration-related requirements that might be specified by law), producing biased estimates of the coefficients of interest. As such, Chapman et al. (2018) suggest that subsidies allocated by the central government are less likely to require collaboration with third parties as a precondition of receiving support. By contrast, local subsidies are more likely to require collaboration as an eligibility condition, since local politicians may seek to foster research collaborations at the local level, thereby strengthening the network-capabilities of local agents (Afcha, 2011).[25] Second, despite the explanations provided in Sections 3 and 5.2.2 on the adequacy of operationalizing the *activating signal* as the combined amount of selective and automatic subsidies, from a theoretical point of view, the amount raised through a competitive procedure might be better correlated with the awardee's quality and innovation potential. Combining the above two issues, first, the estimated influence of the *pointing signal* may be inflated by a simultaneity bias, potentially driven by the selective procedures managed by local governments; second, the variables *Total subsidized R&D amount (t-1)* and *Total subsidized R&D amount (t-2)* may include three different *activating signals*, namely, the amount of central government selective subsidies, the amount of local government selective subsidies, and the amount of automatic subsidies. As such, for corporate collaborations, we decompose the *activating signal*, and thus substitute the variables *Total subsidized R&D amount (t-1)* and *Total subsidized R&D amount (t-2)* with six different variables that measure at time *t-1* and *t-2* the amount of central government selective subsidies (*R&D amount by central government selective subsidies (t-1)* and *R&D amount by central government selective subsidies (t-2)*), the amount of local government selective subsidies (*R&D amount by local government selective subsidies (t-1)* and *R&D amount by local government selective subsidies (t-2)*), and the amount of automatic subsidies (*R&D amount by automatic subsidies (t-1)* and *R&D amount by automatic subsidies (t-2)*). For academic collaborations, we test whether the estimated *pointing signal* is affected by simultaneity bias, thus substituting the variables *Selective R&D subsidy (t-1)* and *Selective R&D subsidy (t-2)* with four variables capturing the awarding of central government selective subsidies (*Central government selective R&D subsidy (t-1)*, *Central government selective R&D subsidy (t-2)*), local government selective subsidies (*Local government selective R&D subsidy (t-1)*, and *Local government selective R&D subsidy (t-2)*). The descriptive statistics of selective subsidies administered by the central government and by local authorities, as well as those of automatic subsidies, are provided in Table 8.

As shown in column (5), the amount raised through selective subsidies from central and local governments is more likely to foster a corporate collaboration, in line with the stronger signal fit of raising money through a competitive vis-à-vis an automatic procedure (Lerner, 1999; Meuleman and De Maeseneire, 2012). The average amount awarded by type of subsidy as shown in Table 8 suggests that the *activating signal* may not depend on the monetary value of the award as much as on the nature of the subsidization scheme, which appears to play an important informative role. However, it should be noted that the combined monetary amount from both selective and automatic subsidies used to measure the *activating signal* in the baseline models (see Table 4) has a higher marginal effect on the likelihood of establishing a corporate collaboration than the amounts raised from central and local government selective subsidies. The estimated semi-elasticities (i.e., δ*Corporate collaboration*/δln(*R&D amount by central government selective subsidies (t-2)*)) at the median value, and the 75° and 90° percentiles of the subsidized amount for those firms awarded a subsidy from the central government are equal to +4.6%, +6.1% and +7.4%, respectively. The same figures for local subsidies are similar in terms of point estimate but with a larger variance. These numbers are lower than those in Table 4 (+5.2%, +6.7% and +8.2%, respectively).[26]

Turning to the *pointing signal*, in column (6), our estimates show that its influence holds for selective subsidies administered by the central government only. Given that selective subsidies administered by local governments are more likely to require a collaboration ex-ante, this finding reassures us that the estimated influence of the *pointing signal* in Table 4 is unlikely to be driven by simultaneity. By contrast, central government selective procedures typically show a higher level of competition among applicants than local procedures, and thus the strength of the signal is likely to be stronger.

Third, as anticipated in Section 4.2, the unbalancing of our dataset may be due to an attrition problem. In other words, if exited firms are less likely to form collaborations, and subsidy-related variables are negatively correlated with firm exit (i.e., firms awarded a subsidy are more likely to survive due to, for instance, additional resources obtained), the influence of subsidy-related variables on the likelihood of forming a collaboration in the population of Spanish firms might be

[23] We argue here that the total amount raised through subsidies (still a regressor in our model specification in Table 7) may contribute, together with past investments in innovative inputs, to an increase in innovation efficiency for three main reasons: first, investments in new inputs allow either obtaining more innovative outputs with the same input costs or the same innovative output with a less intensive use of inputs. Second, additional financial resources may be used to speed up the development of technologies via, for instance, hiring complementary research and human capital, better management practices, and improved organizational structures. Third, additional money helps sustain patent-related costs.

[24] As in Table 6, timing effects of subsidies reported in Table 7 might differ from those in Table 4, due to the much lower number of observations following the inclusion of the variable for innovation efficiency; indeed, the sensitivity of results to sample size is likely to be higher in short panels (as used in this study).

[25] Besides fostering enterprise investments in R&D activities, many regional support programs explicitly aim to promote collaborative R&D projects between firms and public research centers (Sanz-Menéndez and Cruz-Castro, 2005; Segarra-Blasco et al., 2008), so as to stimulate the formation of regional innovation systems and open innovation networks. Examples of such programs include (i) the largest subsidy schemes in the Basque Country in the period 2001-2008, such as INTEK, GAITEK, INNOTEK (OECD, 2011); (ii) the financial aid programs for R&D and industry-academic cooperation of the Technology Corporation of Andalusia established in 2005; (iii) grants for cooperative R&D projects and contracting R&D activities to universities that were part of Catalunia's 2005-2008 Research and Innovation Plan (OECD, 2010); and (iv) the III and IV Regional Plan of Scientific Research and Technological innovation (2000-2003 and 2005-2008, respectively) in the Comunidad de Madrid. According to the Spanish national institute of statistics (INE), in 2008, these four regions accounted for approximately 70% of national R&D expenditure (Cruz-Castro et al., 2018).

[26] An interesting and surprising result is that the coefficient of *Automatic R&D subsidy (t-2)* is positive and statistically significant at the 5% level in column (5). This result differs from all the other models estimated in this study that show no statistical significance for automatic subsidies. This is also the only model indicating that the award of a subsidy acts as a positive *pointing signal* on the likelihood of establishing a corporate collaboration. A possible interpretation could relate to the lack of significance of *R&D amount by automatic subsidies* at time *t-1* and *t-2*. It might be the case that the significance of this latter effect vanishes as it is captured by the combination of the dummy variable *Automatic R&D subsidy*, measuring the award of tax credits, and *R&D intensity*, whose numerator, R&D expenses, is used to calculate the amount of tax credits. Both these variables are positively and significantly associated with the likelihood of establishing a corporate collaboration in column (5).

Table 7
Main robustness checks.

	Substantive effect vs signal effect				Simultaneity and activating signal decomposition		Attrition	
	(1) Corporate collaboration	(2) Academic collaboration	(3) Corporate collaboration	(4) Academic collaboration	(5) Corporate collaboration	(6) Academic collaboration	(7) Corporate collaboration	(8) Academic collaboration
Selective R&D subsidy (t-1)	−0.3043	0.2159	−0.4072	0.2489	−0.1513		−0.3784	0.3566*
	(0.2366)	(0.1985)	(0.2732)	(0.2143)	(0.1982)		(0.2432)	(0.1970)
Selective R&D subsidy (t-2)	−0.3196*	0.4282**	−0.4049*	0.5537**	−0.4027**		−0.2522	0.5119***
	(0.1769)	(0.1779)	(0.2243)	(0.2216)	(0.1958)		(0.1830)	(0.1752)
Automatic R&D subsidy (t-1)	0.1025	−0.3025	0.0403	−0.1193	0.0845	−0.0744	0.1116	−0.1382
	(0.2123)	(0.2227)	(0.3144)	(0.2734)	(0.2653)	(0.1968)	(0.2105)	(0.2078)
Automatic R&D subsidy (t-2)	0.0288	−0.0464	0.1615	0.0810	0.5420**	−0.1835	−0.0168	−0.0404
	(0.1909)	(0.2052)	(0.2513)	(0.2527)	(0.2313)	(0.1931)	(0.1968)	(0.1927)
Central government selective R&D subsidy (t-1)						0.5110***		
						(0.1713)		
Central government selective R&D subsidy (t-2)						0.2896		
						(0.1883)		
Local government selective R&D subsidy (t-1)						0.1805		
						(0.1933)		
Local government selective R&D subsidy (t-2)						0.0285		
						(0.2003)		
Total subsidized R&D amount (t-1)	0.0948*	0.0221	0.1248*	0.1419		−0.0526	0.0895	−0.0356
	(0.0566)	(0.0500)	(0.0745)	(0.0868)		(0.0429)	(0.0574)	(0.0481)
Total subsidized R&D amount (t-2)	0.0980**	−0.0066	0.1060**	−0.0301		0.0389	0.0843*	−0.0088
	(0.0447)	(0.0461)	(0.0521)	(0.0542)		(0.0422)	(0.0466)	(0.0421)
R&D amount by central government selective subsidies (t-1)					0.0346			
					(0.0370)			
R&D amount by central government selective subsidies (t-2)					0.0811**			
					(0.0372)			
R&D amount by local government selective subsidies (t-1)					−0.0513			
					(0.0440)			
R&D amount by local government selective subsidies (t-2)					0.0977*			
					(0.0545)			
R&D amount by automatic subsidies (t-1)					0.0706			
					(0.0574)			
R&D amount by automatic subsidies (t-2)					−0.0684			
					(0.0497)			
Past collaboration experience	1.1843***	1.7544***	1.5688***	2.3211***	1.1962***	1.5412***	1.2707***	1.6052***
	(0.1696)	(0.1634)	(0.2572)	(0.2671)	(0.1448)	(0.1387)	(0.1537)	(0.1422)
Age	−0.1892*	0.0585	−0.3341**	0.2101	−0.1152	0.0746	−0.1799*	0.0325
	(0.1096)	(0.1242)	(0.1671)	(0.1672)	(0.0896)	(0.0916)	(0.0942)	(0.1015)
Size (t-1)	−0.0264	0.1599**	−0.0766	0.0234	0.0820	0.1921***	0.0699	0.1746***
	(0.0709)	(0.0761)	(0.1194)	(0.1227)	(0.0594)	(0.0638)	(0.0629)	(0.0659)
R&D intensity (t-1)	0.8957	1.0447	0.4119	0.5677	2.5261***	0.4909**	2.3035***	0.3701
	(0.8325)	(1.0321)	(1.1659)	(1.6749)	(0.2069)	(0.2157)	(0.2165)	(0.2302)
Patents (t-1)	−0.6182	−0.0249	−0.0520	0.1812	−0.1637*	0.1476	−0.1898**	0.1541

(continued on next page)

Table 7 (*continued*)

	Substantive effect vs signal effect				Simultaneity and activating signal decomposition		Attrition	
	(1) Corporate collaboration	(2) Academic collaboration	(3) Corporate collaboration	(4) Academic collaboration	(5) Corporate collaboration	(6) Academic collaboration	(7) Corporate collaboration	(8) Academic collaboration
	(0.5196)	(0.5988)	(0.1571)	(0.2241)	(0.0959)	(0.0945)	(0.0952)	(0.0967)
EU project dummy (t-1)	−0.4035	0.2443	−0.5619	0.0980	−0.4086	0.2463	−0.4013	0.1244
	(0.3876)	(0.4551)	(0.4604)	(0.5173)	(0.4022)	(0.3654)	(0.3810)	(0.3995)
Human capital (t-1)	0.6370**	0.4428**	0.6119**	0.5390**	0.4643*	0.5564***	0.4343*	0.5290***
	(0.2875)	(0.2117)	(0.2620)	(0.2583)	(0.2553)	(0.2002)	(0.2541)	(0.1943)
Debt/Equity (t-1)	0.0280	0.0137	0.0977	−0.0255	−0.0059	−0.0125	0.0014	−0.0041
	(0.0415)	(0.0517)	(0.0931)	(0.0770)	(0.0146)	(0.0175)	(0.0160)	(0.0218)
Debt/Sales (t-1)	−0.2832	−0.0191	−0.4570	0.0786	−0.2616*	−0.0230	−0.2945**	−0.0285
	(0.1869)	(0.1307)	(0.4060)	(0.0512)	(0.1427)	(0.0549)	(0.1493)	(0.0574)
ROA (t-1)	0.0429	0.4272	−0.5828	0.1950	0.0341	0.0090	0.0173	0.1739
	(0.3686)	(0.3019)	(0.4809)	(0.4295)	(0.2372)	(0.0288)	(0.0286)	(0.2240)
Listed (t-1)	1.6450***	0.4721	1.2744**	−0.1612	0.7654***	0.0557	0.6550**	−0.0501
	(0.5513)	(0.3777)	(0.5755)	(0.4676)	(0.2847)	(0.2810)	(0.2982)	(0.3098)
Group (t-1)	−0.0837	−0.1218	0.1435	0.2136	−0.1525	0.1132	−0.2743*	0.1092
	(0.1566)	(0.1762)	(0.2318)	(0.2456)	(0.1408)	(0.1443)	(0.1489)	(0.1489)
Foreign controlled (t-1)	0.0922	−0.1887	0.0096	0.0932	0.0956	−0.1851	−0.0122	−0.1899
	(0.1798)	(0.1711)	(0.2812)	(0.2593)	(0.1630)	(0.1472)	(0.1725)	(0.1527)
Family (t-1)	0.2768	0.2577	0.2353	0.2624	0.2892**	0.0561	0.2837**	0.0554
	(0.1782)	(0.2133)	(0.2982)	(0.3297)	(0.1447)	(0.1442)	(0.1386)	(0.1434)
Limited liability (t-1)	−0.1570	−0.4902***	−0.1899	−0.6216**	−0.0742	−0.1529	−0.0806	−0.1578
	(0.1747)	(0.1833)	(0.2765)	(0.2875)	(0.1305)	(0.1339)	(0.1364)	(0.1365)
Competition (t-1)	0.0009	−0.0028	−0.0016	−0.0030	0.0003	−0.0017	−0.0001	−0.0023
	(0.0028)	(0.0031)	(0.0041)	(0.0041)	(0.0021)	(0.0023)	(0.0023)	(0.0024)
Patents/R&D (t-1)	6.7474	2.7726						
	(7.0443)	(7.6678)						
Patents/Total subsidized R&D amount (t-1)			−1.3705	0.7232				
			(1.0983)	(1.6959)				
IMR_{exit}							−0.0181	0.0199
							(0.0231)	(0.0277)
Year dummies	Y	Y	Y	Y	Y	Y	Y	Y
Industry dummies	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	979		534		2425		1813	

Regressions estimated with an intercept term. Standard errors in brackets.

* $p < 0.10$.

** $p < 0.05$.

*** $p < 0.01$.

Table 8
Number of beneficiary firms and average monetary amount across different types of subsidies.

Subsidy type	Number of beneficiary firms	Average amount (€) awarded to beneficiary firms
Central government subsidy	107	228,486
Local government subsidy	95	79,226
Automatic subsidy	175	134,243

weaker than that highlighted in our empirical analysis.[27] Thus, we test for the potential presence of attrition in our data by means of the variable addition test explained in Section 6.4. As above, we compute an IMR-type term (IMR_{exit}) by means of a panel probit model where the dependent variable is a dummy variable that equals one if the firm exited the dataset,[28] and as additional regressor, we still use the dummy indicating whether the firm actively applied for R&D tax credits. From a theoretical point of view, the firm's active search for R&D tax credits may be a predictor of firm exit,[29] while, as explained above, the additional regressor may not necessarily be linked to the likelihood of starting a collaboration. Our results are shown in Table 7 (last two columns) and are in line with those in Table 4. As regards the coefficient of $\mathrm{IMR}_{\mathrm{exit}}$, this is not statistically significant, thus reassuring us on the influence of attrition on our findings.

Finally, in Appendix A, we test whether policymakers are likely to decide on the allocation of selective subsidies based on variables not included in our model specifications.

6.5.2. Other robustness checks

First, in columns (1) and (2) of Table 9, we substitute *Size (t-1)* with three size dummies for different size intervals: *Micro*, *Small*, and *Medium* that equal one if the firm has fewer than ten employees, from ten to 49 employees, or from 50 to 249 employees. The baseline category is represented by large firms. It seems that micro firms are less likely to access academic collaborations, and this finding may be explained by the fact that micro firms are less likely to engage in innovation activities (Baumann and Kritikos, 2016), even though their link between R&D, innovation, and productivity does not differ from that of other firms. Our main results still hold.

Second, in the last two columns of Table 9, we substitute *Past collaboration experience* with the variables *Past corporate collaboration experience* (i.e., the firm's previous experience in collaborating with corporate partners) and *Past academic collaboration experience* (i.e., the firm's previous experience in collaborating with academic partners). Differently from Table 5, here we aim to test for the influence of both types of past collaboration experience (i.e., corporate and academic) on each type of collaboration. As shown, while academic collaborations seem to be influenced by past academic collaboration experience only, both types of past collaboration experience influence the likelihood of establishing a corporate collaboration. Results are in line with those in Table 4.[30] Third, in Table B1 (Appendix B), we use two different proxies to measure human capital, and our main results are confirmed. Fourth, automatic and selective subsidies might be awarded at different times, with the former (latter) typically awarded after (before) conducting R&D activities.[31] Even though we allow for two lags in our model specification, the alleged influence of most selective subsidies on the likelihood of collaborating with third parties has more time to materialize than automatic ones. As such, in unreported regressions, we extend our baseline model specification by inserting a third lag for automatic subsidies; results in Table 4 hold. Finally, in unreported regressions, we re-ran our regressions in Table 4 by means of both random effects (RE) probit models[32] and generalized estimating equation (GEE) models. Details are reported in Appendix C.

7. Concluding remarks

This study adopts a signaling lens to analyze the influence of public R&D subsidies on the formation of technological collaborations by recipient firms. Unlike most innovation policy evaluation studies, our work examines the dual nature of signals sent by subsidies, distinguishing between the *pointing signal* emitted by the award of a subsidy, and the *activating signal* emitted by the monetary amount awarded. Our empirical analysis provides evidence that the salience of these distinct signals varies across different receiver types (academic and corporate collaboration partners).

7.1. Implications

This paper contributes to three different research streams. First, we contribute to the literature evaluating the effectiveness of innovation policies by providing new insights in relation to the growing literature on behavioral additionality (e.g., Chapman et al., 2018; Grilli and Murtinu, 2018). Our work offers empirical evidence of the dual signaling function of public R&D subsidies in the context of collaboration formation, above and beyond the substantive benefits of subsidies. The present study provides a possible explanation of why previous empirical works generally support a positive influence of subsidies on academic collaborations while reporting mixed evidence for collaborations with corporate partners (e.g., Maietta, 2015; Miotti and Sachwald, 2003). Indeed, while our analysis consistently shows that universities attend to the signal deriving from the award of a selective subsidy, corroborating prior results, it also indicates that the subsidy-related information that matters to corporates when making collaboration formation decisions relates to the subsidy's monetary amount. This result informs on the ambiguous findings in previous studies that only model subsidies as a

[27] To note is that attrition is not likely to be a serious concern in our data. Indeed, SEPI Foundation, which administers the ESEE survey, aims to minimize attrition issues and maintains the representativeness of the sample with respect to the population. First, it sends reminders to those sampled firms that might hesitate to fill in the questionnaire year after year. Second, every year it incorporates new firms in the panel following the same inclusion criteria as in the base year. This ensures that the survey maintains population coverage across industries and size segments (www. www.fundacionsepi.es/).

[28] In the dataset, we do not have a variable for firm exit. Thus, we use an indirect approach by looking through the time series of employment data. For each firm, if such series displays missing values from a certain year on, we assign a value of one to firm exit in that specific year, whereas firm exit is missing in subsequent years.

[29] As highlighted in several studies on firm exit using the ESEE survey (e.g., Esteve-Pérez et al., 2004, 2018), exit mainly represents one of three outcomes: closure/liquidation, acquisition by another firm, shift to a non-manufacturing industry. A firm's search for R&D tax credits may be due to, for instance: i) the willingness to innovate to be competitive and avoid closing the business; ii) the search for money to pursue or speed up technological development or other innovation activities; iii) the search for money to diversify the business. These potential goals of searching for R&D tax credits are likely correlated with exit.

[30] Compared to Table 4, the only notable exception is the lack of statistical significance of *Selective R&D subsidy (t-1)* in columns (2) and (4).

[31] See, for instance, Invest in Spain: http://www.investinspain.org/invest/wcm/idc/groups/public/documents/documento/mda0/njmw/-edisp/4630560.pdf.

[32] Fixed effects probit models are not a suitable choice due to their inconsistency (Greene, 2004).

Table 9
Other robustness checks.

	Firm size intervals		Partner-specific collaboration experience	
	(1) Corporate collaboration	(2) Academic collaboration	(3) Corporate collaboration	(4) Academic collaboration
Selective R&D subsidy (t-1)	−0.3078	0.2771	−0.2291	0.2619
	(0.2354)	(0.1881)	(0.2301)	(0.1876)
Selective R&D subsidy (t-2)	−0.2660	0.4778***	−0.0893	0.3223*
	(0.1760)	(0.1709)	(0.1629)	(0.1848)
Automatic R&D subsidy (t-1)	0.1320	−0.2058	0.1585	−0.0813
	(0.2045)	(0.2028)	(0.2084)	(0.1967)
Automatic R&D subsidy (t-2)	−0.0146	−0.0507	0.0266	−0.0452
	(0.1892)	(0.1915)	(0.1868)	(0.1978)
Total subsidized R&D amount (t-1)	0.0673	−0.0134	0.0587	−0.0139
	(0.0554)	(0.0448)	(0.0566)	(0.0445)
Total subsidized R&D amount (t-2)	0.0845*	−0.0015	0.0730*	−0.0116
	(0.0449)	(0.0405)	(0.0434)	(0.0426)
Past collaboration experience	1.2342***	1.5800***		
	(0.1441)	(0.1384)		
Past corporate collaboration experience			1.7724***	0.0201
			(0.1255)	(0.1513)
Past academic collaboration experience			0.2614**	1.8838***
			(0.1301)	(0.1169)
Age	−0.1128	0.0877	−0.1217	0.1146
	(0.0872)	(0.0919)	(0.0887)	(0.0839)
Size (t-1)			0.0841	0.1370**
			(0.0560)	(0.0573)
Micro	−0.3852	−1.3711***		
	(0.4653)	(0.4283)		
Small	−0.0850	−0.3295		
	(0.1943)	(0.2146)		
Medium	0.0353	−0.1007		
	(0.1399)	(0.1467)		
R&D intensity (t-1)	2.5009***	0.5100**	1.3918***	0.7916***
	(0.2060)	(0.2149)	(0.1866)	(0.2245)
Patents (t-1)	−0.1464	0.1643*	−0.1059	0.1032
	(0.0940)	(0.0901)	(0.0933)	(0.0877)
EU project dummy (t-1)	−0.3526	0.2026	−0.1038	0.0931
	(0.3771)	(0.4038)	(0.4098)	(0.3636)
Human capital (t-1)	0.4525*	0.5565***	0.3785*	0.3495**
	(0.2533)	(0.1937)	(0.2028)	(0.1568)
Debt/Equity (t-1)	−0.0055	−0.0127	−0.0119	−0.0441
	(0.0135)	(0.0172)	(0.0165)	(0.0339)
Debt/Sales (t-1)	−0.2327*	−0.0158	−0.0462	0.0195
	(0.1402)	(0.0433)	(0.0678)	(0.0451)
ROA (t-1)	0.0207	0.0080	0.0160	0.0771
	(0.0483)	(0.0411)	(0.0204)	(0.1873)
Listed (t-1)	0.8413***	0.2146	0.8401***	0.2432
	(0.2771)	(0.2770)	(0.2549)	(0.3050)
Group (t-1)	−0.1396	0.1956	−0.0768	0.1613
	(0.1399)	(0.1433)	(0.1379)	(0.1327)
Foreign controlled (t-1)	0.0986	−0.1420	−0.0117	−0.1529
	(0.1634)	(0.1423)	(0.1590)	(0.1399)
Family (t-1)	0.3134**	0.0395	0.3234**	0.1182
	(0.1459)	(0.1466)	(0.1565)	(0.1550)
Limited liability (t-1)	−0.0678	−0.1318	−0.2236*	−0.1547
	(0.1294)	(0.1386)	(0.1251)	(0.1247)
Competition (t-1)	0.0001	−0.0019	−0.0000	−0.0018
	(0.0021)	(0.0023)	(0.0021)	(0.0022)
Year dummies	Y	Y	Y	Y
Industry dummies	Y	Y	Y	Y
Obs.	2426		2426	

Regressions estimated with an intercept term. Standard errors in brackets.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

binary variable, without considering the subsidized amount.

Similarly, by distinguishing between the *pointing* and *activating signals*, our study would suggest the existence of a possible signaling role of automatic subsidies. By acting as an *activating signal*, the amount raised through automatic subsidies in combination with that raised from selective schemes can increase the likelihood of subsidized firms establishing a collaboration with corporates. This is an original contribution to prior research modelling automatic subsidies as *pointing signals* only, and hence finding no signaling role (Colombo et al., 2011). The finding that the *activating signal* appears stronger for SMEs might also be due to the role of automatic subsidies in pushing firms to formalize their R&D activities, and hence subject to public oversight, which is a significant shift particularly for SMEs that tend to pursue innovation informally (Santamaría et al., 2009). Thus, the amount of tax credits received might have a stronger information content for smaller firms. However, this result should be treated with caution: our robustness check, decomposing the *activating signal* (see Table 7, column 5), suggests that only the amount raised from selective subsidies influences the likelihood of corporate collaborations. Yet, our main variable for the *activating signal*, based on both selective and automatic subsidies, has a higher marginal effect and is consistently significant across the models. Further research is needed on this point.

Our results also show that the dual influence of subsidies on academic and corporate collaborations is stronger for SMEs, in contrast to the "rich get richer" characterization of signaling, in line with Islam et al. (2018).

Second, this study adds to the alliance literature, in particular, the stream investigating firm-specific factors favoring the formation of collaborations (Gulati, 1999; Shah and Swaminathan, 2008; Stuart, 1998). We focus on the literature on how signals of firm quality may alleviate information asymmetries in "markets for collaborations", thus facilitating the realization of collaborations. Our work therefore complements previous works on patents, star scientists, venture capital financing, and other quality signals (e.g., Luo et al., 2009; Pollock and Gulati, 2007). Unpacking the dual signaling effect of R&D subsidies, our findings suggest that the bridging role of subsidies critically depends on the nature of the collaboration counterparty. Drawing on attention-based view and homophily arguments, we suggest that diverse academic and corporate domains and goals differently influence the information that would-be partners are more likely to act on when making decisions on the viability of the innovating firm and related collaboration. As collaborations with academic and corporate partners appear as distinct phenomena favored by different drivers, we argue that future alliance studies should avoid putting them "in the same bucket".

Third, this study makes a relevant contribution to the literature on signals. To the best of our knowledge, this study is the first offering an empirical application of the distinction between *pointing* and *activating signals* proposed by Connelly et al. (2011). Our results support the dual nature of signals conveyed by public R&D subsidies, and suggest that treating signals monolithically, as is standard in the literature on public R&D funding, might mask considerable heterogeneity in their uncertainty reduction function (in our context, measured by their influence on collaboration formation). By showing that each partner type would seem to attend to one signal but not the other, our findings advance understanding of how receivers perceive and evaluate concurrent signals originating from the same source. Our evidence thus supports the conclusions of Khoury et al. (2013) while contrasting those of Colombo et al. (2019) who find additive signals conveying non-overlapping information in the context of biotech IPOs. Finally, our comprehensive analysis underlines that an accurate investigation of signals calls for the joint examination of signal, signaler, and receiver, and the match among these primary elements.

This paper offers useful policy implications. The differential influence of a subsidy award *per se* and the monetary amount on the likelihood of collaborating with different partner types suggests that a "one-size-fits-all" approach is not an effective solution for policymakers to stimulate collaborative behavior. Depending on the need to foster academic or corporate collaborations, policymakers may differently prioritize advertising the outcomes (e.g., names of winners, amount awarded) of subsidy programs. In line with Grilli and Murtinu (2018), we are not suggesting here that "forcing marriages" between parties is a good policy. Instead, we advocate a more complex role of public authorities in the management of innovation policies, and the diffusion of information to facilitate the matching processes in "markets for collaborations", particularly when the recipients of subsidies are SMEs. As such, we suggest that via the advertisement of subsidy program outcomes, policy makers may behaviorally stimulate the collaborative strategies of economic agents. The amount and type of information diffused may act as a nudge for both innovative firms and potential collaboration partners. On the one hand, exposure to the advertised information may produce a sort of *virtuous circle*, stimulating innovative firms to boost their innovation efforts, so as to increase their chances of winning a selective subsidy and/or a larger amount of subsidized money to place them in the spotlight. On the other hand, an increase in advertised information renders the *pointing* and/or *activating signals* more salient for potential partners, thus stimulating collaborations. More specifically, advertising subsidy program information generates a social reference group (i.e., the subsidized innovative firms) so that potential collaboration partners might more easily identify the optimal counterparty, ultimately reducing their search costs.

For managers, our analysis suggests that beyond funding R&D investments and stimulating innovation outcomes, R&D subsidies help firms form collaborations. When pursuing open innovation strategies, especially in SMEs, managers should consider the possibility of applying to subsidy programs, even if the firm's financial situation does not require it. Once awarded a subsidy, managers are advised to diffuse the information contained in the specific signal to the market, with the final aim of attracting the attention of the desired partner. According to the type of targeted partner, our findings may help managers in "playing with the salience" of the dual signals of subsidies.

7.2. Limitations and directions for future research

This study has several limitations that open up future research avenues. First, due to data constraints, our dependent variables cannot account for the number of collaborations undertaken by each firm in each year. Further, among the firms that did not establish collaborations during the sampled period, our data cannot distinguish those that did not do so due to lack of interest from those that were interested in collaborating but did not manage to consummate a deal (Bianchi and Lejarraga, 2016). Future research should find ways of separating the effects of antecedents on an organization's propensity to enter collaborations from its ability to attract partners, and ultimately access their complementary resources.

Second, our data do not provide granular information about the exact nature of the public support received (whether the subsidy is, for instance, aimed at the development of new knowledge or the implementation of a technology), the specific goal and object of the collaboration formed (whether the collaboration hinges on a research project, a development project, or a mixed R&D project; see Hottenrott et al., 2017), and the identity and characteristics of the partners (e.g., the prestige of the university or the corporate counterparty's industry; whether a collaboration persists with the same partner or whether a firm persistently collaborates but with different partners). In addition, we can only assume that the collaboration formed bears on the subsidized innovation project.[33] We argue that this key issue, which is also assumed in most behavioral additionality studies (Busom and Fernández-Ribas, 2008; Chapman et al., 2018), is not necessary for our conclusions to hold. The motivations underlying partner selection and the establishment of a collaboration go beyond project-level characteristics and include firm-level characteristics (e.g., past financial and innovation performance, collaboration experience), which our analysis controls for.[34] However, future research should investigate the motivations and contents of R&D collaborations and the role of subsidies at a more granular level, using qualitative case studies, quantitative surveys, or experimental data in narrower empirical settings, e.g., within corporations. Further, future research needs to intersect partner identity with the nature of the collaboration (recent, persistent, discontinued) to better understand how intertemporal patterns in different types of collaborations may shape the strategy (and likelihood) of future collaborations and types of partners.

Third, our results for the time lags of subsidy variables seem to vary across the models. While the timing of signal effects is not the focus of our study, future research should specifically investigate when signals start playing a role, and how their strength changes over time, depending on the type of signal, signaler, and receiver, and their combination.

Fourth, despite our extensive robustness checks and efforts in addressing simultaneity and endogeneity issues, we acknowledge that our dataset might include subsidies granted conditional on collaboration. While our data preclude a more fine-grained separation of signaling and the substantive effects of subsidies, we believe our empirical approach provides relevant evidence of the existence of a dual signaling function above and beyond the financial benefits of the subsidy.

Fifth, our data refer to a single country in the pre-crisis period (2001–2007), which may limit the generalizability of our results. While the policy evaluation literature is context-specific by definition (that is, a policy in a specific context at a specific time cannot be fully replicated in another context at a different time, but only provides hints and information on how to (re-)design policy schemes and the expected outcome after the implementation of a specific policy), our research setting allows reliably ruling out that crisis-related external shocks drive our results. However, we recognize that a longer timeframe and a multi-country context would enhance the generalizability of our findings and allow capturing longer-run dynamics and causal effects.

Lastly, future research should investigate whether other quality signals that innovating firms might activate (e.g., patents, top management team members, venture capital financing) have a dual (*pointing* and *activating*) nature, and how they influence a wider set of outcomes than just collaboration formation. It would also be interesting to examine how these multiple signals interact. Further, while our work has considered firm size as a relevant attribute of the signaler, we call attention to the need to explore the role of other factors influencing signal effectiveness, possibly at multiple levels of analysis, such as the country-, industry-, technology-, and partner-specific level.

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[33] We thank an anonymous reviewer for this comment.

[34] The literature on open innovation (Chesbrough, 2006) suggests that there may not be a one-to-one match between a subsidized project and a collaboration because complex and promising projects, such as those receiving competitive subsidies, are likely to require the acquisition and/or sharing of several complementary resources to realize the project's innovation potential and hence an array of collaborations distributed across the innovation value chain (Bayona et al., 2001; Chapman et al., 2018; Laursen and Salter, 2006).

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Appendixes

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