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Drivers of Cooperation in Innovation by Energy Firms in Spain

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Abstract

Innovation by energy firms is critical for facing the energy transition and the challenge of climate change. Innovation is a complex process, and firms increasingly resort to cooperation with other companies and institutions in their innovation activities. In the energy sector, suppliers have always played a very important role in the technological advances of this industry. The objective of this paper is to analyse the determinants for engagement in cooperation in innovation by energy firms. In this analysis, we distinguish by the type of partnership, whether suppliers or research organisations (universities and research centres). We consider the factors proposed by the industrial organisation literature and the reasons given for firms to innovate, to explain decisions to cooperate. For the empirical analysis, we use a sample of energy firms from the Spanish Technological Innovation Panel (PITEC) for the period 2004–2016. To carry out the estimations we use binary models for panel data. In order to correct for endogeneity of the relevant variables, some of which are binary, we have relied on the panel data version of the special regressor method. Our results show the important role of incoming spillovers and innovation objectives related to reducing the environmental impact and meeting environmental regulatory requirements to explain cooperation in innovation by energy firms.

Keywords Energy · Cooperation · R&D · Innovation · Environment

JEL Classification Q40 · Q55 · O31 · O32

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1 Introduction

The transition towards a low-emissions economy is fundamentally reshaping energy industries. On both global and European scales, concerted efforts are underway to harness the full potential of renewable energy sources to substitute conventional fossil fuel generation, which is characterized by a higher environmental impact. Spain exemplifies this trend, as evidenced by data from Red Eléctrica[1], the national system operator. Fifteen years ago, renewable energy generation accounted for scarcely a quarter of total electricity production. In contrast, it now accounts for more than half of total generation. This paradigm shift is not only evident in a change in the energy mix but also in the recent notable increase in the number of operators, resulting from new renewable energy projects.[2]

To achieve net zero, it will be necessary to further accelerate innovation in clean energy technologies (IEA 2023) and reformulate industrial policy and the green agenda (Aghion et al. 2023). Despite the rise in global investment in research and development for clean energy, indicative of heightened climate ambitions among nations, a significant innovation gap persists (Egli et al. 2022; Polzin and Sanders 2020). Innovation is a main driver in the transformation process of energy firms and it is critical for facing the energy transition and the challenges of climate change. Innovation is a complex process and firms use different R&D and innovation strategies to obtain new products and processes. Cooperation in innovation with other partners is an important mechanism to access external knowledge and complementary resources. Energy firms, like firms in other industries, are increasingly engaging in cooperative partnerships.

Empirical research (Abramovsky et al. 2009; Badillo and Moreno 2016; Amoroso 2017) shows that the reasons for cooperation in innovation differ across sectors. The energy industry - a key sector for achieving a net-zero economy - has specific attributes related, among other issues, to its specific regulatory framework and business structure, that may affect the factors leading to engagement in cooperation in innovation. With the rise of renewable energies, storage solutions, and smart grid technologies, fostering collaborations and public support become crucial for advancing innovation in this sector. These differences highlight the need for a specific analysis of the energy sector.

While there is an extensive literature analysing the factors that drive cooperation and the reasons that explain the choice of specific partners for firms in general (see, among others, Belderbos et al. 2004a, b; Cassiman and Veugelers 2005; López 2008; Lara et al. 2020), this is, to the best of our knowledge, the first paper to carry out this analysis specifically for energy firms. The objective of this paper is therefore to examine the determinants for cooperation in innovation by energy firms and in the choice of partners, distinguishing between suppliers (vertical cooperation) and universities and research centres (institutional cooperation). Although energy firms also cooperate with other partners such as competitors or clients, we focus on suppliers and research organisations that are the main partners of cooperation. Suppliers have always played an important role in innovation in the energy sector (Sanyal and Cohen 2009; Jamasb and Pollitt, 2015; Costa-Campi and García-Quevedo 2019) while access to basic research has an important role to achieve environmental innovation objectives.

[1] https://www.ree.es/es/datos/aldia.

[2] (https://www.cnmc.es/sites/default/files/5177925.pdf, *Informe de supervision del mercado peninsular mayorista al contado de electricidad*, *2022.ref: is/de/013*, *published 22/02/ 2024*, *(CNMC, 2024, see pp 64–91).*

Our main research questions focus on understanding the role of incoming spillovers and the environmental objectives of innovation on the decisions of energy firms to cooperate in innovation. We consider two innovation objectives: reducing environmental impacts and meeting environmental regulations. The energy industry has undergone a significant transformation by reducing its environmental impact while complying with regulatory pressures related to climate change targets. These are crucial reasons to innovate (Costa-Campi et al. 2019).

We support our empirical analysis with contributions from the industrial organisation literature and with other frameworks, such as the resource-based view and particularly, in the economics of innovation literature regarding the reasons and objectives for innovation by firms (Cassiman and Veugelers 2002; De Marchi 2012; Teece et al. 1997). The inclusion of these objectives in the analysis provides new insights into the reasons for cooperation and in particular about the role played by environmental and regulatory purposes.

This paper contributes to the literature in different ways. As mentioned above, this is the first paper to examine what drives cooperation in innovation for energy firms. Furthermore, this analysis distinguishes between different partners (suppliers and institutional sources). Secondly, the estimations introduce the reasons why firms innovate, which, to the best of our knowledge, is an area which has not been included in previous analysis. Including these variables allows us to improve our understanding of the reasons for cooperation in innovation. Thirdly, empirical analyses of R&D and innovation in energy firms are frequently constrained by a lack of data (Anadon et al. 2011; GEA 2012; Gallagher et al., 2012). In our empirical analysis, we use a panel of data that provides detailed information about the innovation activities of the firms concerned.

To carry out the estimations, we use the information provided by the Spanish Technological Innovation Panel (PITEC) for the period from 2004 to 2016. The data collected for this panel is based on information taken from the Community Innovation Survey conducted in Spain, adhering to the guidelines of the Oslo Manual of the OECD (OECD 2005). To carry out the estimations we use binary models for panel data. In order to correct for endogeneity of the relevant variables, some of which are binary, we have relied on the panel data version of the special regressor method.

The results of our econometric analysis for energy firms show that incoming spillovers have a positive effect on cooperation in innovation by these firms. In our analysis we have focused on the reasons to innovate related to environmental issues, specifically in reducing environmental impacts and compliance with environmental regulation. The results show the significant role of meeting environmental regulatory requirements in the decisions to cooperate and the importance of reducing environmental impacts as a reason for cooperation in innovation with institutional partners. Our results also show the benefit of distinguishing by partners as this reveals significant differences in what drives the choice of partner.

The paper is organized as follows. The next section reviews the literature and provides a framework to empirically examine what drives cooperation in innovation of energy firms. The third section describes the database and provides information about cooperation in innovation in this industry. This is followed by a presentation of the specification of the model. The fourth section presents the econometric estimations and discusses the results. The paper ends with a concluding section.

2 Framework: Cooperation in Innovation by Energy Firms

2.1 The Fundamentals of Cooperation in Innovation

The importance of cooperative research agreements has been one of the main topics in the literature on the economics of innovation. The theoretical contribution of D'Aspremont and Jacquemin (1988) asserted that when R&D externalities or spillovers are large enough, cooperation in innovation leads to higher R&D spending and, consequently, cooperation has a positive impact on competitiveness and even on economic welfare. Empirical contributions have also revealed the positive influence of cooperation both on the innovative results of firms, and their performance (Van Leeuwen 2002; Janz et al., 2004Sakakibara 1997; Hagedoorn 2002; Belderbos et al. 2004a; Czarnitzki et al. 2007; Laursen and Salter 2006; and Trąpczyński et al. 2018 among others). In this way, cooperation strategy has become something more than an access to innovation that coexists with internal development strategy (to make) or external acquisition strategy (to buy), to become an important source of business competitiveness (Cassiman and Veugelers 2002, 2005; Chistov et al. 2023).

A significant segment of the literature does not only focus on the impact of collaboration on innovation performance, but also on characterizing the decision to collaborate in innovation for firms in general. In this field, the contribution of Barge-Gil (2010) shows that smaller firms and firms outside the high-tech sectors are more likely to be cooperation-based innovators, while Amoroso (2017) argues that the establishment of cooperation agreements is a firm-level process, where a strong sectoral heterogeneity exists.

The role of public institutions is another determinant of cooperation studied by industrial organisation theory. This is especially important in a context of high indebtedness of both public administrations and the private sector, where the financial resources that exist to invest in research and innovation are limited, since research is an investment that involves high risk and uncertainty (Jamasb and Pollitt 2015). Public-private cooperation is essential in a context of uncertainty and high risk. This cooperation leads to greater financial resources being made available and allows for the sharing of knowledge. The cooperation in innovation projects between firms and universities allows firms, especially SME, to take on innovation projects.

The nature and performance gains of cooperation between the university and industry will depend on the characteristics of the firm itself and its pattern of innovation. Lara et al. (2020) compare the innovation performance of companies that have succeeded in developing product innovations in cooperation with universities, with research institutes, and with other types of partners. The results show no distinction between the innovation performance of the cooperation with universities and research centres, while the firms in these two groups achieved better performance in innovation than those firms that entered into collaboration projects with other partners. These results are robust for both SMEs and large firms, although the results show that large firms are more likely to have cooperated with universities and research institutes.

In line with this, Orazbayeva et al. (2019) argue that it is necessary that European, national, and regional policies establish incentives so that the knowledge of the universities located in each territory is used as a strategic asset to increase innovative capabilities and competitiveness. This necessitates not only encouraging the entrepreneurial spirit of the research staff of universities, but also that such research should endeavour to go beyond the innovation stage, and help companies, especially SMEs, to be more innovative.

Theoretical contributions emphasize the positive impact of cooperation between agents (Yang et al. 2021). In addition, several empirical papers that have studied the impact of government R&D subsidies on collaborative innovation between companies (Kleinknecht and Reijnen 1992; Sáez et al. 2002; Kang and Park 2012; Bozeman and Gaughan 2007; Segarra-Blasco and Arauzo-Carod 2008) have found that there is a strong association between government support and cooperation in innovation. However, recently Ahn et al. (2020) show that though government R&D subsidies positively affect innovation collaboration, the relationship has an inverted U-shape that suggests that the impact in highly funded firms was smaller than that in firms that received a more modest amount. In particular, the authors highlight that in a financially comfortable scenario resulting from excessive R&D subsidies, firms might naturally opt for safer and more manageable internal R&D over riskier collaborative innovation efforts.

Other factors which should be taken into consideration include the innovation portfolio of partners, by establishing new types of cooperation in innovation with different kinds of collaborators. In the realm of cooperation, research has demonstrated the critical importance of having a diverse array of collaborators (suppliers, customers, competitors and universities and public research institutions) (Badillo and Moreno 2016; Belderbos et al. 2004b, 2018; Teixeira et al. 2019). Generally, vertical alliances, those between firms operating in related industries within the same value chain, have a significant effect on R&D intensity and technological innovation performance (López 2008; Trąpczyński et al. 2018). Meanwhile, cooperation with suppliers is important to ensure the supply of inputs or components with features (for example in terms of energy efficiency) that may not be readily available on the market (De Marchi 2012). The specialised literature reveals that horizontal technological alliances (with competitors in the same industry) have an inverted U-shaped relationship with innovation performance because of competition. In particular, excessive researching and collaboration can harm firms by complicating coordination and increasing the costs associated with maintaining relationships (Trąpczyński et al. 2018). However, some studies also point out the opportunities and strengths of cooperation among competitors in fostering R&D and innovation. In this regard, various contributions show that competitors have a higher propensity to share complementary resources that allow for the synergistic accumulation of knowledge (Dussauge et al. 2000; Gnyawali and Park 2011).

Beyond the intentional effects of a cooperation strategy on innovation outcomes, the literature also highlights that the integration of new knowledge into the innovation process creates unintentional knowledge flows or spillover effects between firms (Audrestch, and Feldman 1996; Cassiman and Veugelers 2002; Egli et al., 2022). Additionally, there is a consensus regarding the two major types of spillovers: incoming spillovers which impact the rate of innovation within the firm, and appropriability spillovers which affect the firm's ability to appropriate the returns from innovation. Overall, the empirical literature supports the positive impact of firms valuing incoming spillovers on the likelihood of cooperation, while the effect of appropriability problems remains ambiguous (Cassiman and Veugelers 2002; López 2008; Badillo and Moreno 2016).

2.2 Cooperation in Innovation in the Energy Sector

The transition to a net-zero economy requires accelerating both the deployment of existing clean energy technologies and the development of new ones. However, the energy sector, despite its importance within the economy, has traditionally shown a low level of expenditure on R&D (GEA 2012). Expenditure data on R&D in the energy sector declined sharply in the late nineties and continued until the second decade of this century (IEA, 2023; Sanyal and Cohen 2009). Some studies have linked this reduction with the restructuring of the electricity industry after the 1980s and 1990s with the liberalization process (Kim et al. 2012; Sanyal and Cohen 2009 and Sterlacchini 2012), while other studies point out that the main barrier hampering innovation in the energy sector is the market dominance of incumbents (Costa-Campi et al. 2014). In particular, this reduction is particularly evident from 1996 to 2008 (IEA 2023) due to a decline in use of nuclear energy - despite its substantial investment in R&D -, compared to an increase in combined cycle energy supplies. That explains the minimal R&D and innovation investment during the period, as well as the nascent introduction of renewable energies. This has not been able to compensate for the drop in internal investment in nuclear energy R&D and innovation. However, new evidence indicates that this trend has shifted significantly, and as of 2020, the total public R&D and innovation budgets for investment in Spain have increased considerably, especially in renewable energy sources and hydrogen and fuel cells (IEA 2023). This change is largely a result of environmental regulations with the purpose of achieving a net-zero economy and of ambitious green recovery programs, implemented in response to the Covid-19 pandemic in the European and Spanish context.

One of the key particularities of innovation in the energy sector is that, given that energy is a homogenous product, innovation strategies focus on efficiency aimed at reducing costs with the objective of increasing margins and achieving differentiation in contracts (Jamasb and Pollitt 2008). A second characteristic of R&D and innovation in the energy sector is that beyond energy utility companies, firms in other sectors, and particularly equipment suppliers, invest significantly in innovation (Sanyal and Cohen 2009; Jamasb and Pollit, 205; Costa-Campi and García-Quevedo). This context added to a technological change marked by the development of renewable energies, storage, and the smart grid, which require quick reactions to implement collaboration ventures and support from public institutions to boost innovation in the energy sector. The achievement of environmental and cost objectives and compliance with environmental regulation during the green energy transition require changes in innovation strategies and the accessing of new skills through external R&D and collaboration in innovation with other firms and stakeholders (Ghisetti et al. 2015; De Marchi 2012; Jakobsen and Clausen 2016; Araújo and Franco 2021). Those particularities reveal that examining the drivers for engagement in cooperation in innovation by energy firms deserves special attention. However, in recent years, the literature on cooperation in innovation in the energy sector has focused mostly on renewable energy (RE) sources. Christensen et al. (2019) contrast collaboration patterns of RE and non-RE innovators and find that RE innovators show a higher tendency to collaborate, and with a more diverse set of partners. However, the study does not find a strong relationship between collaboration and performance for RE innovators. On the other hand, Yun et al. (2019), using patents and financial data over a five-year period (2008–2012) for 50 solar photovoltaic (PV) technology firms found both technological diversification and R&D collaboration can have a positive impact on performance, reducing the degree of technological uncertainty.

Lacerda and van den Bergh (2020), based on an analysis of original survey results, examine the role of different knowledge sourcing strategies for innovation in solar and wind power. The paper finds that solar power innovation benefits from a broad research strategy drawing on a large number of external knowledge sources, while wind power innovation tends to thrive through intensive use of a more limited number of external sources. In a study looking at the overall energy sector, Rennings and Rammer (2009) use data from the German Community Innovation Survey (CIS) for the period 2002 to 2004 and find a positive association between cooperation and innovation in the energy sector.

The role of the cooperation between public institutions and private institutions on energy innovation is well established in the literature. Focusing on green energy technologies, Popp (2017) sheds light on the value of knowledge flows between academia, the private sector and governmental research by means of US patent data, and finds that those articles most highly cited by other scientific articles are also more likely to be cited by future patents. He also finds that the research performed at government institutions appears to play an important translational role linking basic and applied research. Interestingly, Popp (2017) finds that research in the energy sector may take longer to progress to a commercialized product. Also, for the energy sector Ardito et al. (2019) find evidence of a significant positive impact of public R&D funding on the number of patents, but no significant effect on patent quality measured by the number of citations. Although in a different economic and regulatory context, Raghutla and Kolati (2023) also revealed that public-private partnerships, R&D investments, and political cooperation enhance renewable energy in China and India.

In summary, beyond traditional utility companies, significant investments for innovation also come from equipment suppliers. With the rise of renewable energies, storage solutions, and smart grid technologies, fostering collaborations and public support becomes crucial for advancing innovation in this sector. Despite acknowledging the importance of improving the speed of innovation in the energy sector, existing studies have primarily focused on cooperation determinants for firms in general, overlooking sector-specific characteristics that may not be universally applicable. Energy sector firms exhibit distinct attributes shaped by regulatory frameworks, business structures, and national energy technology mixes. These factors underscore the intricate dynamics of technological change, collaboration, and institutional support crucial for driving innovation, particularly amid global sustainable development initiatives. Against this backdrop, this study seeks to contribute to the literature by analyzing the determinants of engagement in cooperation in innovation among Spanish energy firms and particularly the role of spillovers and the environmental objectives of innovation.

2.3 Drivers of Cooperation in Innovation

In the previous two subsections we have provided a general framework about cooperation in innovation and explained some specificities of R&D and cooperation in innovation in the energy industry. Departing from this framework and from the industrial organisation literature and taking also into account some insights from the resource-based-view and the economics of innovation approaches, we propose, in this subsection, a selection of drivers of cooperation in innovation. These variables will be used in our econometric estimations.

In particular, our main research questions focus on understanding the effects of incoming spillovers and the environmental reasons to innovate to explain the decisions to cooperate in innovation by energy firms.

The industrial organisation literature has focused on the role of spillovers in cooperation in innovation. Theoretical models and empirical works from this literature have shown the important role of incoming spillovers. Incoming spillovers refer to external information flows and they are usually measured via the assessment of the importance that firms attribute to the different sources of publicly available information for undertaking its innovation activities (Cassiman and Veugelers 2002; López 2008; Badillo and Moreno 2016). Cooperation in innovation and in R&D may help to manage these information and knowledge flows. IEA (2020) emphasizes that spillovers play a significant role in the transition towards net zero emissions and provides examples of the importance of spillovers in the development of energy technologies and how they may accelerate progress in clean energy innovation. Nemet (2012), Stephan et al., (2020) and Kolesniskov et al. (2024) also show the important role of knowledge spillovers in advances in energy technologies.

Regarding the reasons to innovate, we consider two environmental objectives. The objectives of innovation are related with R&D and innovation strategies and behavior of the firms (Jakobsen and Clausen 2016; Costa-Campi et al. 2019). Deciding on the objectives of innovation is usually the starting point from which to carry out innovation activities (Jakobsen and Clausen 2016). In energy firms, the implementation of new processes has been the main motivation to innovate. Nevertheless, and because of the importance of the transition to a climate neutral economy, reducing environmental impacts or meeting environmental regulatory requirements are currently crucial reasons to innovate for energy firms (Costa-Campi et al. 2019). As Popp (2019) states, regulatory pressures spur firms to develop new ways to improve environmental performance. Also, Popp et al. (2010) provide some specific results for energy firms showing that regulatory stringency favours the adoption of new technologies. More recently, Ribeiro et al. (2023), employing a difference-in-differences estimation on a panel dataset for 21 European countries found that regulation has positively impacted innovation, measured by patents, in the sector of electricity distribution and transmission.

The literature (Cassiman and Veugelers 2002; Belderbos et al. 2004b; López 2008; Badillo and Moreno 2016) also proposes other reasons to innovate that we have included as control variables. The first set of these variables are the main characteristics of the firms, the size and age. Larger firms are more likely to engage in cooperation in innovation. They have more absorptive capacity, and they are more likely to carry out various R&D projects that may require cooperating in innovation with different partners (Fritsch and Lukas 2001; Belderbos et al. 2004b). We also consider the age of the firm. Older firms may have more absorptive capacity and therefore are more likely to cooperate. However, younger firms are more likely to develop new products and be active in emerging sectors which may require complementary resources to overcome information obstacles in order to drive cooperation in innovation. Therefore, our findings indicate there is not a clear relationship between the age of the firm and cooperation in innovation.

The second set of control variables are specific to R&D and innovation activity of the firm. According to the industrial organisation literature, R&D intensity is a main factor to explain cooperation in innovation (Fritsch and Lukas 2001; Belderbos et al. 2004a; Badillo and Moreno 2016). R&D intensity indicates internal innovative activity, and it is also a measure of absorptive capacity. In addition, public funding for business R&D projects from different sources (regional and local subsidies, national and European subsidies) are also potential drivers of cooperation in innovation. Many R&D subsidies aim to increase R&D cooperation, particularly with research institutions. To limit the simultaneity bias for these variables of subsidies we use the lags of these variables. Finally, we also consider outgoing spillovers, measured through applications for patents, that are related to the ability of the firm to appropriate the returns of innovation. When firms are more effective in this appropriation, they are more likely to cooperate (Cassiman and Veugelers 2002). Nevertheless, the results of the empirical literature are not conclusive.

The next two variables correspond to obstacles to innovation that are related to the resource-based-view approach in the management literature. These two variables are the costs of innovation - whether they are very high - and the lack of information on technology. In both cases, these variables are measured through assessment by the firms of the importance of these obstacles in preventing or hampering their innovation activities (see Table 4 in the Appendix).

3 Data and Model Specification

3.1 Database and Descriptive Statistics

The dataset used in this paper is a sub-sample of the Technological Innovation Panel (PITEC) for Spanish firms. PITEC provides exhaustive information on the characteristics and innovative activities for more than 12,000 Spanish firms for the period 2003–2016 (unfortunately, 2016 is the last year with available information for this panel, which has been discontinued). The data collected through PITEC feeds the Community Innovation Survey (CIS) and it is carried out annually following the guidelines of the OECD's Oslo Manual. While the CIS database offers information on cross-section observations, PITEC provides a large panel of firms and it has frequently been used to carry out empirical analysis on innovation, including innovation in energy firms (Costa-Campi et al. 2014, 2019). We consider energy firms all those with activities related to the generation, transmission, distribution and retailing of energy (NACE 35 Rev. 2 classification). Unfortunately, PITEC does not provide any additional disaggregation.

The first year PITEC provides information for is 2003. However, the data for that year is incomplete since many variables were only incorporated into the questionnaire in 2004. Nevertheless, as we use the lags of some independent variables in the estimations, we also use the data for 2003 to avoid the loss of information before removing all the observations corresponding to that particular year. After applying these filters, 665 observations are available for 97 energy companies forming an unbalanced panel for the period 2004–2016 of which 30 are present at least 12 years (17 are present during the whole period of analysis). On the other hand, 20 firms are observed only once.

The firms in the Spanish energy industry (see Table 1 for descriptive statistics) are on average quite large, with a mean size of more than 600 employees (See Table 4 in the Appendix for the definition of the variables and Table 5 for the matrix of correlations, also in the appendix).

More than half of these firms have engaged in cooperation in innovation (mean of 61% for the whole period). The two main partners in those collaborative relationships have been research organisations and suppliers. Cooperation in innovation of energy firms increased notably from 2004 to 2016 (Fig. 1). While in 2004 around 50% of energy firms reported cooperation in innovation, this percentage was greater than 70% in 2016. This increase in cooperation in innovation activities has also happened for research organisations and suppliers. Energy firms also collaborate with other partners such as competitors or clients, but to a lesser degree. While 54.0% and 42% have cooperated with research organisations and suppliers respectively, the percentages for competitors and clients are only of 26% for competitors and 17% for clients. Taking into account the small size of our sample we consider it preferable to focus our analysis only on research organisations and suppliers.

In addition, we show (Fig. 2) the evolution of the importance that energy firms consider for two objectives of innovation, to reduce environmental impact and compliance with environmental, health and safety regulations as a "proxy" of meeting environmental regulation (Costa-Campi et al. 2014). There has been a notable increase in the percentage of firms that consider these reasons to innovate of high importance. In particular, in 2016, around 60% of the firms considered that the reduction of their environmental impact was of high importance, more than 20% points than in 2004.

3.2 Model Specification and Methodology

Several crucial strategic decisions taken by firms, such as cooperation with other firms and institutions in their innovation activities, can be described as discrete choices. Although these are rather complex decisions that require the thorough consideration of factors affecting demand and supply, firm-level databases generally only include data on the final choice made by the firms as a dichotomous decision. One advantage of this approach is that whenever the variable that we want to model is binary, it is natural to think in terms of probabilities. In a latent variable context, discrete choice models are traditionally viewed as models suitable for estimating parameters of interest when the dependent variable is not fully observed (see for instance Wooldridge (2010) and Train (2009) for general expositions of the approach, and Haghani et al. (2021) for a recent review of the literature and applications).

To analyse the firms' decisions to engage in cooperation in innovation, we assume that firm's i (i=1,…,N) propensity to cooperate y^*_{it} in time t (t=1,…,T) is an unobservable continuous variable with an unknown distribution of errors. The propensity to cooperate is modelled as a function of some explanatory variables (x'_{it}) such that $y^*_{it} = \alpha_i + \beta x'_{it} + \varepsilon_{it}$ and where α is a constant and ϵ the error term. From this specification, the underlying latent model is

$$y_{it} = \begin{cases} 1 & \text{if} \quad y^*_{it} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

Therefore, $\Pr(y_{it} = 1) = \Pr(y^*_{it} > 0) = \Pr(\varepsilon_{it} > -\beta x'_{it} - \alpha_i) = F(\alpha_i + \beta x'_{it})$. This equation holds as long as the density function describing F is symmetric around zero. The standard solution has been to use logistic or normal cumulative distribution functions that constrain $F(.)$ to be between zero and one. These are the logit and probit models, respectively.

Initially, we assume that the decision to cooperate with different types of partners is independent. However, as this assumption may not hold due to strategic decisions by firms, we will relax it and test for the degree of interdependence of the decision to cooperate with different partners. Hence, in Eq. 1, y_{it} corresponds to the dichotomous decision to engage or not in cooperation in innovation activities with a particular type of partner. As pointed out above, we consider cooperation in innovation with any partner as well as cooperation in innovation with two specific partners, suppliers (vertical cooperation) and universities and R&D centres (institutional cooperation). This means that we will estimate three separate equations, one for each type of partner.

The selection of the variables in x'_{it} is based on, as pointed out in the previous section, the industrial organisation literature and on the resource-based-view and the economics of innovation approaches, taking into account some specific characteristics of the energy industry (see Table 4 in the Appendix for the description of the variables).

In non-linear panel data models, the presence of individual effects complicates estimation significantly (Baltagi 2008). Although there are several causes to explain these difficulties, the most relevant is known as the incidental parameters problem and is caused by only having T observations to estimate each α_i, so that as N grows the estimate of α_i remains random (Chamberlain 1980). The usual solution to this incidental parameter issue is to find a minimal sufficient statistic for the α_i which does not depend on the β. This can be done by using a conditional likelihood approach in the case of the logit model, but no solution exists yet for the probit. This suggests that we can either use the pooled data and lose the information provided by the panel structure or use random effects models.

The choice of random effects is not innocuous, since estimation relies on several assumptions, such as strict exogeneity, the independence between α_i and x'_{it} and normally dis-

Table 1 Descriptive statistics

	Variable	Obs.	Mean	Std. dev.	Min	Max
1	Cooperation in innovation	511	0.611	0.488	0	1
2	Cooperation with suppliers	511	0.417	0.494	0	1
3	Cooperation with research organisations	511	0.540	0.499	0	1
4	Spillovers	511	0.400	0.273	0	1
5	Environment	511	0.417	0.494	0	1
6	Regulation	511	0.319	0.467	0	1
7	Size (in logs)	665	5.132	1.908	0.7	9.0
8	Age (in logs)	606	3.143	0.969	0	4.8
9	R&D intensity	663	0.039	0.401	0	7.7
10	Regional subsidies	665	0.229	0.420	0	1
11	National subsidies	665	0.292	0.455	0	1
12	European subsidies	665	0.218	0.413	0	1
13	Lack of information	665	0.059	0.235	0	1
14	High innovation costs	665	0.186	0.390	0	1
15	Patents	665	0.134	0.341	0	1
16	Basicness or R&D	511	0.437	0.314	0	1
17	Importance of internal information	511	0.779	0.300	0	1
18	International market	665	0.259	0.438	0	1
19	Industry average of spillovers	665	0.402	0.052	0.328	0.523
20	Industry average of importance of internal info	665	0.039	0.058	0.002	0.184
21	Industry average of environment	665	0.423	0.096	0.296	0.630
22	Industry average of regulation	665	0.322	0.079	0.180	0.452

tributed error components. In particular, the strict exogeneity assumption implies that correcting for an explanatory variable that is not strictly exogenous is quite difficult in this setting (Wooldridge, 2010). This is particularly relevant in our model since the literature dealing with cooperation in innovation has identified several variables, mainly related to spillovers, as endogenous. In addition, as we are also particularly interested in the role of innovation objectives, we believe that these variables can also be considered as endogenous.

Given the difficulties that arise when trying to estimate binomial response models, such as the probit, where one or more explanatory variables are endogenous, the existing approaches to solve this problem rely on alternatives such as the linear probability model (LPM) with instruments (ignoring the binary outcome), maximum likelihood estimation (MLE) or the control function (CF) approach. While all of these estimation techniques have their strengths and weaknesses, the drawbacks are seldom recognized.

In the case of the LPM, when some explanatory variables are endogenous they will be correlated with the error. Given an adequate set of instruments, this can be estimated by any instrumental variables approach such as 2SLS or IV-GMM. However, as this method is based on standard regression, the zero conditional mean assumption applies. In the case of endogenous variables, the corresponding mean conditional assumption applies not only for the exogenous variables, but for the whole set of instruments including the exogenous elements. Hence, a serious problem arises, as the error cannot be independent of any regressors, even exogenous, unless the matrix of independent variables consists of a single binary regressor, which is rare in current applied economics research and definitely not in our case. An additional well recognised drawback from LPM is that the fitted values are not constrained to lie in the unit interval. In this case, the predicted probabilities can take values below zero and above one (Wooldridge 2010).

As an alternative to LPM, a MLE of a binary outcome with endogenous regressors can be implemented, allowing them to be continuous, discrete or limited. The requirements, however, are that the link function can be fully specified, along with a fully parametrised joint distribution of the errors. Moreover, MLE does not allow for control of heteroskedasticity of unknown form in the model's error process. These requirements are difficult to fulfil, except under very specific circumstances.

Estimations based on CF first estimate the model of endogenous regressors as a function of instruments and then use the errors from this model as an additional regressor in the main model. This approach is more general than maximum likelihood as the first stage function can be semiparametric or nonparametric, and the joint distribution of the errors need not be fully parameterized. However, a substantial limitation of CF methods in this context is that they generally require the endogenous regressors to be continuous. Otherwise, this violates the assumptions necessary to derive estimates of the first stage error term.

In summary, both MLE and CFE of binary outcome models require the first stage model to be correctly specified. This is an important limitation of these approaches, as the resulting estimators will generally become inconsistent. An alternative method that allows for binary dependent and binary endogenous variables is the special regressor estimator (SRE) (Lewbel 2000; Dong and Lewbel 2015). The method works by including a special regressor in the model, V, with the following properties: it is exogenous, appears as an additive term in the model, it is continuously distributed and has a large support[3].

[3] The stata command "sspecialreg" estimates the special regression estimator of a binary outcome with one or more binary endogenous variables.

Let's define D as an observed binary variable representing the decision to cooperate in innovation. Let X be a vector of explanatory variables (observed regressors), and β a corresponding coefficient vector, with ε an unobserved error. In some models, X would include binary explanatory variables as well. In general, X could be divided into a set of endogenous variables (X^e) possibly correlated with ε, and a set of strictly exogenous variables (X^0).

A binary choice or model can be written as

$$D = I(X\beta + \varepsilon \geq 0) \tag{2}$$

where $I(\cdot)$ is the indicator function, which is identical to (1). This latent variable approach is that employed in a binomial probit or logit model, with normal or logistic errors, respectively. The binary choice special regressor proposed by Lewbel (2000) has the form

$$D = I(X^e\beta_e + X^0\beta_0 + V + \varepsilon \geq 0)$$

which is the same basic form for D as in the MLE or CF approaches. In this case, however, the special regressor V has been separated from the other exogenous regressors, and its coefficient normalized to unity.

Given a special regressor V, the only additional requirements are those applicable to linear instrumental variables methods: a valid set of instruments and the fulfilment of the rank condition. The special regressor method imposes fewer assumptions on the distribution of errors, particularly the errors in the 'first stage' equations for the endogenous variables, than do CFE or MLE estimation methods. Therefore, SRE may be expected to have larger standard errors and lower precision than other methods, when those methods are valid. However, if a special regressor V can be found, the SRE method will be valid under much more general conditions than the MLE and CFE methods.

The special regressor method is a widely used estimation procedure applied to a large number of binary choice models such as selection and treatment models (Lewbel 2007), binary panel models with fixed effects (Honore and Lewbel 2002; Ai and Gan 2010), dynamic choice models (Heckman and Navarro 2007), market equilibrium models of multinomial discrete choice (Berry and Haile 2011), models of entry games and matching games (Khan and Nekipelov 2018; Fox and Yang 2018), and more. In the field of innovation, Iandolo and Ferragina (2021) have used it to study the relationship between firms' internationalisation and innovation performance.

4 Estimation and Results

4.1 Results and Discussion

The results of the estimation (Table 2) for the factors that explain that energy firms cooperate in innovation without distinguishing between any specific partner confirm the important role of incoming spillovers in explaining the decision to engage in cooperation in innovation by energy firms. The analyses for firms in other sectors, industry and services, have also shown a positive and significant relationship between incoming spillovers and the decision to cooperate (Cassiman and Veugelers 2002; López 2008; Badillo and Moreno

Table 2 Estimates of a panel binary choice special regressor model for cooperation in innovation

	(1) Total	(2) Suppliers	(3) Institutional
Spillovers	0.296***	0.0602	0.213***
	(0.0817)	(0.0837)	(0.0750)
Environment	0.0321	0.0722	0.0984**
	(0.0387)	(0.0519)	(0.0459)
Regulation	0.0928*	0.124*	0.159***
	(0.0517)	(0.0679)	(0.0541)
Size (in logs)	0.120***	0.121**	0.154***
	(0.0432)	(0.0497)	(0.0431)
Age (in logs)	-0.0385	0.0497	0.00904
	(0.0288)	(0.0314)	(0.0277)
R&D Intensity	0.0254	0.0149	0.0102
	(0.0981)	(0.141)	(0.148)
Regional/local subsidies (t-1)	0.0162	0.00385	0.0293
	(0.0198)	(0.0207)	(0.0214)
National subsidies (t-1)	0.0591**	0.0276	0.0647**
	(0.0248)	(0.0303)	(0.0266)
European subsidies (t-1)	0.00775	0.00783	0.0375**
	(0.0179)	(0.0201)	(0.0189)
Lack of Information	0.0960**	0.130***	0.195***
	(0.0400)	(0.0423)	(0.0434)
High innovation costs	-0.00172	0.0167	0.00364
	(0.0259)	(0.0303)	(0.0220)
Patents	0.0124	0.000151	0.0165
	(0.0174)	(0.0188)	(0.0208)

Notes: Marginal effects obtained using the average index function (Lewbel, Dong and Yang, 2012) from a panel data binary choice special regressor estimation method (Lewbel and Dong 2015) with kernel density function. The standard errors for marginal effects are calculated using the bootstrap method with 100 replications, and are showed in parentheses with *, ** and *** indicating statistical significance at 90, 95 and 99% levels, respectively. The special regressor is the log of size. Data are for the period 2004–2016. The number of firms is 48. The number of observations is 390. The dependent variable is 1 if the company cooperates in innovation with partner i (i=Total, Suppliers, Institutional) and 0 otherwise. The variables indicating spillovers, environment and regulation are considered endogenous and instrumented. Instruments include: basicness of R&D; the importance of the company's own information; a dummy variable taking the value 1 if the firm perceives its relevant market to be international and zero otherwise; the industry average of spillovers; the industry average of R&D intensity; the industry average of the relevance of environment and regulation as innovation objectives; and the lags of the two innovation objectives variables. The results of the tests of validity of instruments are presented in Table 6 in the Appendix. Table 4 in the Appendix includes the definitions of the independent variables

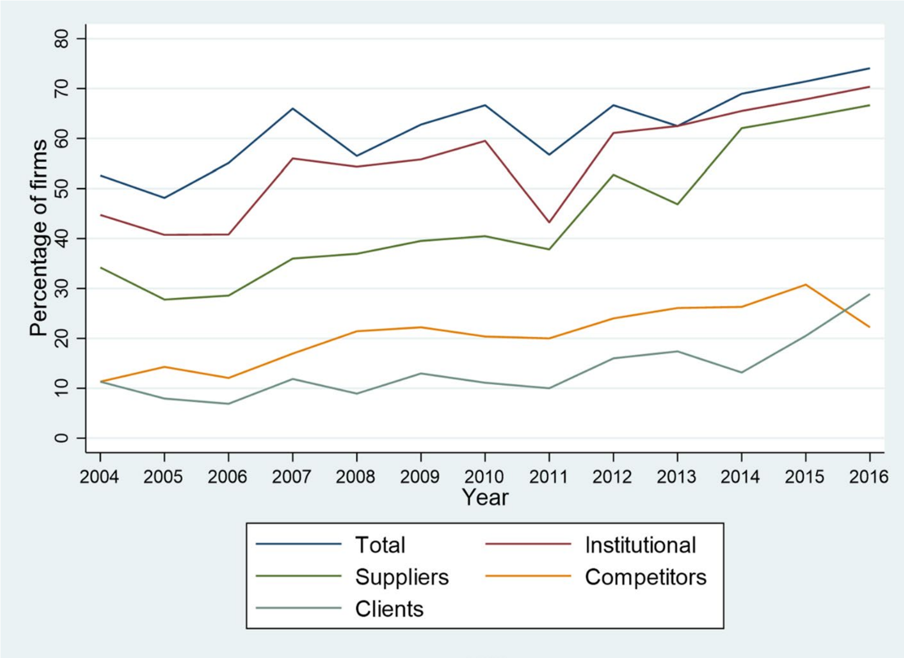

Fig. 1 Cooperation in innovation of Spanish energy firms. 2004–2016.
Source: PITEC and own elaboration. Note: Institutional refers to research organisations (universities and research centres)

2016). According to the marginal effects from our estimations, a higher importance given to incoming spillovers increases the probability of cooperation by approximately 30 percentage points. This is a similar result to those obtained by López (2008) in his preferred estimation for industry Spanish firms (25 percentage points) but below the marginal effects in other estimations (Cassiman and Veugelers 2002; Abramovsky et al., 2009). Therefore, when energy firms consider publicly available information of high importance, they are more likely to cooperate.

The inclusion in the estimations of the environmental objectives of innovation provide new insights into the reasons why firms decide to engage in R&D cooperation. Firms that consider compliance with environmental regulation as an important reason to innovate are more likely to cooperate in innovation (marginal effect on the probability of cooperation of 9.3 percentage points). This result is coherent with recent works (Ribeiro et al. 2023) that show that regulation positively affects innovation in electricity companies, as we have pointed out in Sect. 2. Reducing their environmental impacts to meet with the current regulations is at present a significant driver of innovation for energy firms. Nevertheless, this was not the traditional driver of innovation activities in energy firms, and it is very likely that they need to use external knowledge and to cooperate with other partners to innovate.

Regarding the control variables, the results show, firstly, that large firms tend to cooperate more. This is a common result in this empirical literature when analysing manufacturing and services firms (Badillo and Moreno 2016) and it is also confirmed for energy firms in our empirical analysis.

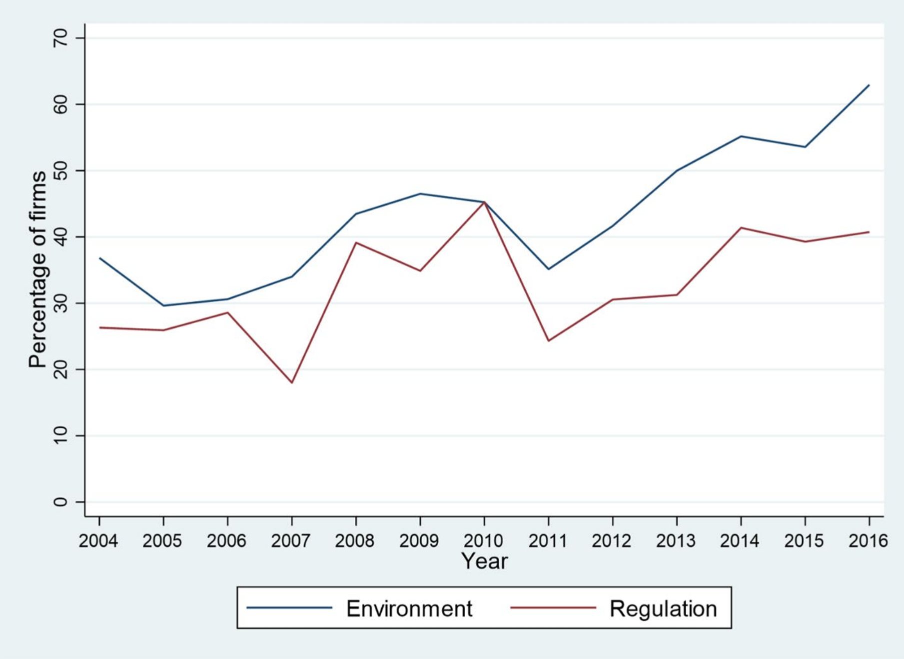

Fig. 2 Innovation objectives of Spanish energy firms. 2004–2016. Source: PITEC and own elaboration

Secondly, there is not a significant relationship between R&D intensity and engagement in cooperation in innovation. Although the common hypothesis is that the firms which are most intensive in R&D will benefit most from cooperation in innovation and therefore their propensity towards R&D cooperation will be greater, the results from the empirical analysis are not conclusive. For Spain in particular, Badillo and Moreno (2016) find a significant effect of internal R&D intensity for the service sector but not for industrial firms. Similarly, López (2008) in his preferred estimation, does not find that R&D intensity increases R&D cooperation. The results of our estimations also show that receiving public R&D subsidies from the national government increases the likelihood of cooperation in innovation.

Thirdly, the two barriers to innovation included in the estimations; the lack of information on technology and the existence of high innovation costs, have different relationships with the decision to cooperate. While the firms that consider the lack of information an important barrier to innovation are more likely to cooperate, the existence of high innovation costs does not affect the decisions taken by energy firms to engage in cooperation. The energy firms are large and it does not seem that financial constraints hamper their R&D and innovation activities (Salies 2010; Costa-Campi et al. 2014).

The results of the estimations (Table 2) for the different types of partners, suppliers and research organisations (universities and research centres), highlight the importance of considering the heterogeneity of R&D cooperation strategies in energy firms, as has been shown for non-energy firms (Belderbos et al. 2004b; Badillo and Moreno 2016).

Although some factors are common to explain the cooperation in innovation of energy firms with suppliers and research organisations, there are also substantial differences.

Table 3 Estimates of a multivariate probit model for cooperation in innovation

	(1)	(2)
	Suppliers	Institutional
Spillovers	1.623***	1.534***
	(0.379)	(0.365)
Environment	0.0695	0.373*
	(0.239)	(0.223)
Regulation	0.854***	0.623***
	(0.242)	(0.240)
Size (in logs)	0.218***	0.172***
	(0.0615)	(0.0581)
Age (in logs)	0.327***	-0.0142
	(0.0839)	(0.0790)
R&D Intensity	0.0687	-0.191
	(0.212)	(0.204)
Regional/local subsidies (t-1)	0.135	0.571***
	(0.187)	(0.191)
National subsidies (t-1)	-0.123	0.284
	(0.186)	(0.193)
European subsidies (t-1)	0.640***	0.570***
	(0.200)	(0.215)
Lack of Information	0.170	-0.148
	(0.379)	(0.360)
High innovation costs	-0.0504	0.0748
	(0.196)	(0.196)
Patents	0.611***	0.105
	(0.224)	(0.245)
û	-3.115***	-2.766***
	(0.736)	(0.754)
Constant	-3.652***	-2.051***
	(0.448)	(0.400)

Notes: Coefficients of a multivariate probit regression. Standard errors are showed in parentheses with *, ** and *** indicating statistical significance at 90, 95 and 99% levels, respectively. Data are for the period 2004–2016. The number of firms is 52. The number of observations is 413. The Log likelihood is -683.829. Wald test: Chi-sq(46) = 482.18 with Pval = 0.000. Likelihood test: Chi-sq(6) = 135.78 with Pval = 0.000 The dependent variable is 1 if the company cooperates in innovation with partner i (i = Suppliers, Institutional) and 0 otherwise. The variables indicating spillovers, environment and regulation are considered endogenous and instrumented. Instruments include: basicness of R&D; the importance of the company's own information; a dummy variable taking the value 1 if the firm perceives its relevant market to be international and zero otherwise; the industry average of spillovers; the industry average of R&D intensity; the industry average of the relevance of environment and regulation as innovation objectives; and the lags of the two innovation objectives variables. The variable û indicates the predicted residuals for an auxiliary equation on spillovers, following a control function approach. Endogeneity of the variables environment and regulation is controlled for by estimating a multivariate probit with four equations, one for each type of cooperation and one for each type of innovation objective. The full results of the multivariate model are presented in Tables 7 and 8 in the Appendix. Table 4 in the Appendix includes the definitions of the independent variables

Regarding the role of incoming spillovers, the estimations for specific partners are consistent with the general estimations and, in general, with the findings of this literature that have highlighted the importance of this factor in explaining engagement in R&D cooperation.

Nevertheless, the effects of spillovers are only significant when the cooperation of energy firms is with institutional partners (universities and research centres) and not when the cooperation is with suppliers. The estimated marginal effect shows an increase in the probability of cooperation by approximately 21 percentage points for institutional partners. This is again a similar magnitude to the one obtained by López (2008) for Spanish industrial firms although it is below that of the marginal effects estimated by Badillo and Moreno (2016) for the same sector (92 percentage points) and service firms (72 percentage points). This is a common result in the empirical literature. Since the work of Cassiman and Veugelers (2002), we know that incoming spillovers have a stronger effect on the probability of cooperation in innovation with research organisations than with other partners. Concretely, Cassiman and Veugelers (2002) and López (2008) found that it is the only partner where there is a positive effect of incoming spillovers while in Abramovsky et al. (2009) and Badillo and Moreno 2016) the effect is greater than for other partners such as suppliers, customers or competitors. This result shows, as Cassiman and Veugelers (2002) point out, that the firms which consider that the pool of publicly knowledge is highly important for their innovation activity are more likely to benefit from collaboration with research organisations, and it suggests that energy firms value access to the research and the knowledge generated in universities and research centres positively.

The estimations provide information about the reasons for innovating that explain cooperation in innovation. The energy firms that consider it very important to meet environmental regulation as an objective of innovation are more likely to cooperate with suppliers. This reason for innovating is also important to explain cooperation with universities and research centres but, in addition, in these cooperative agreements, the aim of innovation concerned with reducing environmental impacts is also significant (marginal effect on the probability of cooperation of 9.8 points). This result suggests that firms resort to external partners to be able to innovate in the field of environmental impact, a relatively new area for them. With these collaborations, firms may access the skills and basic knowledge that the research organisations have regarding scientific advances in environmental research. For example, Popp (2017) highlights the importance of knowledge flows between research organisations and firms on fostering energy innovation and point out that collaborative research has positive effects on renewable energy research.

Regarding the control variables, the results show that the parameter for size is positive and significant in both cases, confirming that larger firms are more prone to cooperate. In contrast, age is only significant in the cooperation with suppliers showing that older and more established firms, as is traditional in the energy industry, have close relationships with these partners that play an important role in technological change in energy.

The results confirm that R&D intensity does not play a significant role in engagement in R&D cooperation for energy firms and the parameter is not significant for either of the two types of partners. The analysis for specific partners provides more information about the effects of public subsidies to finance business R&D in the energy sector. Public R&D subsidies, national and European, are related to cooperation with universities and research centres but not with suppliers. R&D subsidies are particularly important to incentivise R&D cooperation with research organisations that are more focused on basic R&D than firms.

Finally, the results also confirm that high innovation costs do not seem to be a barrier that hampers or prevents energy firms from cooperating in innovation. Instead, the estimations again show the importance of analysing R&D cooperation with different agents separately. Our results point out that firms try to overcome the negative effects of the lack of information on technology in their innovation activities by resorting to other firms (suppliers) and institutions (universities and research centres).

To check the consistency of our results, we have carried out some complementary estimations. Firms can engage simultaneously in cooperation agreements with suppliers and universities and research centers. To consider this issue, we have used a biprobit specification that allows for systematic correlations between choices for these two cooperation types (Belderbos et al. 2004b). The estimations (Table 3) show that the coefficient for the correlation parameters is positive and significant. This suggests the existence of complementarity between the cooperation in innovation with these two types of partners. The results of the estimations hold for our main variables of interest, incoming spillovers and the role of the objectives of innovation.

5 Conclusions

The objective of this paper has been to analyse the drivers of cooperation in innovation of energy firms focusing particularly on the effects of incoming spillovers and the environmental objectives of innovation. In this analysis we have considered that these drivers may be different depending on the partner and we have distinguished between suppliers (vertical cooperation) and universities and research centres (institutional cooperation). The selection of the variables for the empirical analysis is grounded mainly in the industrial organisation and economics of innovation literatures. The empirical analysis has been carried out with a panel data for Spanish energy firms for the period 2004–2016. To carry out the estimations we have used binary models for panel data. In order to correct for endogeneity of the relevant variables, some of which are binary, we have relied on the panel data version of the special regressor method.

The descriptive statistics show that energy firms are increasingly cooperating in innovation with different partners and that the two main partners are suppliers and research organisations. The results of our econometric analysis confirm the importance of the role of incoming spillovers to explain cooperation in innovation by energy firms. In our analysis we have included the reasons for innovation related with reducing environmental impacts and meeting environmental regulatory requirements. The results support the importance of these two objectives of innovation which lead to cooperation. Our estimations also show that size and public support are, similarly to the analyses carried out for manufacturing firms, positively related with cooperation in innovation in energy firms. Our results reveal significant differences in the drivers for the choice of partner. Cooperation in innovation with suppliers is related mainly with the objective of innovation in regard to compliance with environmental regulation. In contrast, cooperation in innovation with research organisations is undertaken to innovate for meeting these regulatory requirements as well as for reducing environmental impact.

From our results, policy recommendations can be made in the field of innovation focused on energy and institutional collaboration. The scope of the energy transition objectives leads energy companies to carry out the necessary innovations that arise from this process. Cooperation in these innovation projects is shown to be an effective solution for companies and for energy policy in the face of the commitment to net zero emissions by 2050.

Formulating effective policies for the mitigation of climate change involves implementing a policy based on public-private collaboration, sharing objectives between companies and public administrations, searching for joint solutions in innovation and focusing the instruments of energy policy towards specific objectives. The findings of this paper show that regulation is one of the determining factors in cooperation, a result in line with the function that regulation has in pursuing energy policy objectives. This mission is manifested not only in its impact on cooperation in innovation projects but also in its relationship with the environment. Hence, the opportunity opens for the transitional energy policy to incorporate cooperation in innovation focused on environmental objectives. The results also suggest that public policies should promote cooperation in innovation of the firms with universities and research centres for the benefit of the environment. Cooperation with research organisations may help to develop long-term strategies with returns for society as a whole, whilst retaining some of the incentives and objectives of innovation of the firms.

Our study has several limitations. Firstly, it would have been helpful to have more recent data regarding the decisions energy firms take to cooperate in innovation in the current framework of the energy transition. Unfortunately, as we pointed out in Sect. 3, the last year with available information for the PITEC is 2016. Secondly, we have focused on the determinants of the decisions made to cooperate in innovation. A promising line of research would be to examine the effects of this cooperation between energy firms, suppliers and universities and research centres on the performance of energy firms. Thirdly, we have included R&D subsidies from different levels of government as control variables. Our results suggest that some of these R&D subsidies have positive effects on the decisions to cooperate. Nevertheless, a proper assessment of the potential causal effects would require other methods as, for example, quasi-experimental procedures, to deal with the sample selection and endogeneity problems that the evaluation of public subsidies faces. Finally, we have focused on our analysis in Spain. The energy sector varies significantly from one country to another, and to carry out similar analysis for other countries would help to compare the results and to increase our understanding about the decisions to cooperate in innovation of energy firms.

6 Appendix

See Tables 4, 5, 6, 7, and 8.

Table 4 Definition of the variables

Variable	Description
Cooperation in innovation	Dummy = 1 if the firm has cooperated in some of its innovation activities with other firms or institutions
Cooperation with suppliers	Dummy = 1 if the firm has cooperated in some of its innovation activities with suppliers
Cooperation with research organisations	Dummy = 1 if the firm has cooperated in some of its innovation activities with universities or research centres

Table 4 (continued)

Variable	Description
Spillovers (incoming) (1)	1 minus sum of the scores of importance that the firm attributed [number between 1 (high) and 4 (not used)] to the following information sources for undertaking its innovation activities: conferences, trade fairs, exhibitions; scientific journals and trade/technical publications; professional and industry associations; rescaled from 0 (unimportant) to 1 (crucial)
Environment (2)	Dummy = 1 if the firm considers the innovation objective of reducing environmental impact of high importance
Regulation (2)	Dummy = 1 if the firm considers the innovation objective of meeting environmental, health and safety regulations of high importance
Size	Number of employees
Age	Years the firm has been operation in the market
R&D intensity	Internal R&D expenditures as a percentage of sales
Regional subsidies	Dummy = 1 if the firm has received an R&D subsidy from a regional or local government
National subsidies	Dummy = 1 if the firm has received an R&D subsidy from the central government
European subsidies	Dummy = 1 if the firm has received an R&D subsidy from the European Union
Lack of information on technology (3)	Dummy = 1 if the firm considers this barrier to be of high importance
High innovation costs (3)	Dummy = 1 if the firm considers this barrier to be of high importance
Patents	Dummy = 1 if the firm has applied for a patent
Basicness or R&D	1 minus sum of the scores of importance that the firm attributed [number between 1 (high) and 4 (not used)] to the following information sources to carry out its innovation activities: universities or other higher education institutions, government or public research institutions and technological centres; rescaled from 0 (unimportant) to 1 (crucial)
Importance of internal information	Dummy = 1 if the firms consider the company's own information of high importance for its innovation process
International market	Dummy = 1 if the firm perceives its relevant market to be international
Industry average of spillovers	Mean of incoming spillovers in the energy industry
Industry average of importance of internal info	Mean of the importance of internal information in the energy industry
Industry average of environment	Mean of the importance of this objective of innovation in the energy industry
Industry average of regulation	Mean of the importance of this objective of innovation in the energy industry

(1) We use the same definition of Badillo and Moreno (2016) that follows the proposal of Cassiman and Veugelers (2002) to measure the importance of publicly available information for the innovation activities of the firms (incoming spillovers). The question of the CIS to construct this variable is: "During the three years …, how important to your enterprise's innovation activities were each of the following information sources?" (High, medium, low, not used)

(2) The question of the CIS for the objectives for products and process innovations is: "How important were each of the following objectives for your activities to develop product or process innovations during the three years ….?" (High, medium, low, not relevant)

(3) The question of the CIS for the barriers to innovate is: "During the three years …. how important were the following factors in preventing your enterprise from innovating or in hampering your innovation activities?" (High, medium, low, not experienced)

Table 5 Correlation matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
2	0.67	1																			
3	0.86	0.60	1																		
4	0.30	0.31	0.33	1																	
5	0.33	0.29	0.38	0.30	1																
6	0.21	0.21	0.24	0.32	0.49	1															
7	0.39	0.41	0.38	0.25	0.19	0.00	1														
8	-0.01	0.12	-0.06	0.02	0.02	-0.02	0.05	1													
9	0.06	0.07	0.04	0.11	-0.02	0.07	-0.06	0.00	1												
10	0.26	0.16	0.31	0.16	0.20	0.04	0.17	-0.21	0.09	1											
11	0.39	0.33	0.45	0.28	0.30	0.09	0.38	-0.07	0.01	0.41	1										
12	0.37	0.41	0.44	0.21	0.30	0.08	0.34	-0.14	0.03	0.37	0.46	1									
13	-0.03	0.04	0.00	0.12	0.11	0.10	-0.12	0.02	-0.02	-0.01	-0.11	0.04	1								
14	-0.01	-0.07	-0.03	-0.04	0.07	0.00	-0.20	0.02	-0.04	-0.08	-0.12	-0.06	0.28	1							
15	0.22	0.30	0.26	0.16	0.15	0.08	0.30	-0.13	0.05	0.28	0.41	0.37	-0.08	-0.08	1						
16	0.49	0.42	0.58	0.55	0.38	0.24	0.37	-0.05	0.13	0.34	0.52	0.41	-0.05	-0.03	0.25	1					
17	0.36	0.28	0.33	0.27	0.30	0.21	0.21	-0.11	0.01	0.09	0.23	0.21	-0.14	-0.04	0.15	0.33	1				
18	0.17	0.28	0.20	0.18	0.09	0.10	0.24	0.07	0.04	0.07	0.21	0.19	-0.09	-0.15	0.17	0.23	0.11	1			
19	0.04	0.12	0.06	0.18	0.08	0.00	0.02	0.02	0.05	0.00	-0.04	0.11	0.13	0.13	0.06	0.10	0.05	0.05	1		
20	-0.01	0.03	-0.03	0.03	0.02	-0.03	0.02	0.06	0.18	0.05	0.00	0.10	-0.04	-0.05	0.03	-0.01	-0.01	0.00	0.20	1	
21	0.10	0.21	0.17	0.08	0.22	0.11	0.07	0.25	0.04	0.01	0.07	0.16	0.15	0.13	0.12	0.15	0.02	0.12	0.39	0.10	1
22	0.06	0.13	0.11	0.02	0.15	0.16	0.04	0.16	0.00	0.01	0.05	0.10	0.05	0.07	0.08	0.10	0.04	0.08	0.08	-0.10	0.74

Table 6 Tests of under- and weak identification for cooperation in innovation

Regression for total cooperation					
Results for first-stage regressions					
			Test for:		
			Underidentification		Weak identification (1)
Equation:	F(11, 323)	P-val	SW Chi-sq(9)	P-val	SW F(9,323)
Spillovers	12.89	0.0000	70.65	0.0000	7.41
Environment	16.28	0.0000	76.15	0.0000	7.99
Regulation	7.94	0.0000	46.04	0.0000	4.83
Results for main model					
Underidentification test			Chi-sq(9) = 39.38		P-val = 0.0000
Weak identification test			3.82 (2)		
Weak-instrument-robust inference					
Anderson-Rubin Wald test			F(11,323) = 4.78		P-val = 0.0000
Anderson-Rubin Wald test			Chi-sq(11) = 55.73		P-val = 0.0000
Stock-Wright LM S statistic			Chi-sq(11) = 47.92		P-val = 0.0000
Regression for suppliers					
Results for first-stage regressions					
			Test for:		
			Underidentification		Weak identification (1)
Equation:	F(11, 323)	P-val	SW Chi-sq(9)	P-val	SW F(9,323)
Spillovers	12.09	0.0000	64.65	0.0000	6.78
Environment	15.16	0.0000	77.78	0.0000	8.16
Regulation	7.84	0.0000	47.14	0.0000	4.95
Results for main model					
Underidentification test			Chi-sq(9) = 39.54		P-val = 0.0000
Weak identification test			3.84 (2)		
Weak-instrument-robust inference					
Anderson-Rubin Wald test			F(11,323) = 3.83		P-val = 0.0000
Anderson-Rubin Wald test			Chi-sq(11) = 44.62		P-val = 0.0000
Stock-Wright LM S statistic			Chi-sq(11) = 39.47		P-val = 0.0000
Regression for institutional					
Results for first-stage regressions					
			Test for:		
			Underidentification		Weak identification (1)
Equation:	F(11, 323)	P-val	SW Chi-sq(9)	P-val	SW F(9,323)
Spillovers	12.85	0.0000	64.10	0.0000	6.73
Environment	15.41	0.0000	72.62	0.0000	7.62
Regulation	7.73	0.0000	44.57	0.0000	4.68
Results for main model					
Underidentification test			Chi-sq(9) = 38.15		P-val = 0.0000
Weak identification test			3.69 (2)		
Weak-instrument-robust inference					
Anderson-Rubin Wald test			F(11,323) = 5.33		P-val = 0.0000

Table 6 (continued)

Regression for institutional		
Results for first-stage regressions		
	Test for:	
	Underidentification	Weak identification (1)
Anderson-Rubin Wald test	Chi-sq(11) = 62.08	P-val = 0.0000
Stock-Wright LM S statistic	Chi-sq(11) = 52.54	P-val = 0.0000

(1) This needs to be compared to the Stock-Yogo weak ID F test critical values. However, the existing critical values are for a single endogenous regressor, while in our model we have three

(2) Cragg-Donald Wald F statistic. See note (1)

Table 7 Correlation of errors between the equations of the multivariate probit model

	Suppliers	Institutional	Environment
Institutional	**0.757***(0.115)**		
Environment	-0.187 (0.153)	-0.0879 (0.130)	
Regulation	-0.342** (0.154)	-0.135 (0.126)	**0.913*** (0.116)**

Note: the correlation between the error terms of the decision to cooperate with suppliers and the decision to innovate to overcome environmental regulatory constraints is negative, meaning that there could be some unobserved factors affecting the decision to cooperate with this type of partners and this innovation objective in the opposite direction. The results, however, control for this endogenous relationship. On the other hand, the correlation of the errors of the two decisions to cooperate and the two innovation objectives are positive, showing a strong complementarity

Source: own elaboration

Table 8 Tests of under- and weak identification for cooperation in innovation (multivariate probit model)

Regression for suppliers					
Results for first-stage regressions					
			Test for:		
			Underidentification		Weak identification (1)
Equation	F(5, 358)	P-val	SW Chi-sq(9)	P-val	SW F(9,323)
Spillovers	24.11	0.000	125.96	0.000	24.11
Results for main model					
Underidentification test			Chi-sq(5) = 94.22		P-val = 0.0000
Weak identification test			24.11 (2)		
Weak-instrument-robust inference					
Anderson-Rubin Wald test			F(5,358) = 2.11		P-val = 0.0063
Anderson-Rubin Wald test			Chi-sq(5) = 44.62		P-val = 0.0051
Stock-Wright LM S statistic			Chi-sq(5) = 39.47		P-val = 0.0057
Regression for institutional					
Results for first-stage regressions					
			Test for:		
			Underidentification		Weak identification (1)
Equation:	F(5, 358)	P-val	SW Chi-sq(5)	P-val	SW F(5,358)
Spillovers	24.11	0.0000	125.96	0.0000	24.11
Results for main model					
Underidentification test			Chi-sq(5) = 94.22		P-val = 0.0000
Weak identification test			24.11 (2)		

Table 8 (continued)

Regression for institutional		
Results for first-stage regressions		
	Test for:	
	Underidentification	Weak identification (1)
Weak-instrument-robust inference		
Anderson-Rubin Wald test	F(5,358)=6.55	P-val=0.0000
Anderson-Rubin Wald test	Chi-sq(5)=34.22	P-val=0.0000
Stock-Wright LM S statistic	Chi-sq(5)=31.35	P-val=0.0000

(1) The Stock-Yogo weak ID F test critical values for single endogenous regressor and 5% maximal IV relative bias is 18.37

(2) Cragg-Donald Wald F statistic for 5% maximal IV relative bias is 18.37

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