Innovation, environmental sustainability and economic development: DEA-Bootstrap and multilevel analysis to compare two regions

Abstract

Innovation and environmental sustainability are key elements in countries' development, essential to ensuring their continuing competitiveness in an increasingly globalized market. Similarly, at the regional level, these elements mark the difference between higher/lower growth; as such, the evaluation of innovation processes is very useful for orienting innovation policies towards those regions that need additional strategies to develop potential improvements. This study proposes the use, in a first stage, of DEA-Bootstrap and the Malmquist Index to analyse the innovation efficiency level in Spanish and Italian regions during the period 2004-2012. In the second stage, multilevel regression is used to analyse the relationship between efficiency, environmental sustainability and economic development. The results show great differences between the territories of the two countries analysed, confirming the need to establish differentiated policies that encourage the adoption of innovation practices in regions whose efficiency scores have shown a lack of rigour in the use of their resources, i.e. south Italian and Spanish regions. Furthermore, it has been shown that the stringency of environmental policies positively affects innovation efficiency, with a positive relationship found between development, innovation and environmental sustainability.

Keywords: Innovation; Development; Sustainability; DEA; Multilevel Regression

JEL: O3, O4, Q5, C3, C6

1. Introduction

Literature has verified the link between research and development (R&D) expenditure, innovation and a country's productivity (Baumann and Kritikos, 2016; Fu et al., 2018; Mohnen, 2019). According to the European Commission (2010) any growth strategy needs to foster investment in knowledge creation, where R&D and innovation play a relevant role (Orlando et al., 2020). However, the impact of these investments is not uniform across territories and countries. Pegkas et al. (2019), in a research conducted in the European Union, concluded that those Member States with higher GDP per capita have more innovative firms, with a higher concentration in the Nordic and Western

European countries, where R&D spending has enabled them to strengthen their international competitiveness.

The needs arising in more industrialized regions are triggering their conversion into knowledge economies, where innovation is the main driver of sustainable economic growth (Cancino et al., 2018; Ferraris et al., 2018; Franceschelli et al., 2018). This process requires ongoing support from policies promoting research into and implementation of the advances that ensure these regions' hegemony over other areas. It is a crucial issue when it comes to marking the differences between territories in the same country, requiring measurements that allow an objective assessment of the results achieved. Decision-making bodies need to be aware of possible inefficiencies in the use of R&D resources in order to avoid technological delays that prevent them from harnessing synergies between the various innovation activities. In short, there is a need for indicators that analyse the efficiency levels of R&D activities and facilitate an understanding of their possible determinants, in order to help guide policies that foster the best use of the resources employed (Chen et al., 2011).

Over the last two decades, various studies on regional innovation systems have been carried out (Carayannis et al., 2017; Dolereux and Porto-Gomez, 2017; Berman et al., 2020), also providing evidence of the need for instruments to assess performance (Janger et al., 2017; Yu et al., 2020). Innovation has sometimes been quantified using a single indicator such as patent statistics (Hauser et al., 2007; Di Cagno et al., 2016; Panda and Sharma, 2019) or with a set of territorially-focused indicators in response to the different innovation systems (Pinto, 2009; Capello and Lenzi, 2013). In addition, a number of synthetic indexes have been developed, which allow a comparative analysis at national level (Bloomberg Innovation Index, Global Innovation Index, European Innovation Scoreboard) and regional level (the European Regional Innovation Scoreboard(RIS) has been published annually for over a decade). However, these indexes have flaws that limit their use. For example, the excessive correlation between some of their components means they cannot properly capture all aspects of innovation linked to each territory (Schibany and Streicher, 2008; Hauser et al, 2018).

In this context, this research aims to analyse the nexus between innovation efficiency, the environmental policies adopted by countries, and regional development. In doing so, the study focuses on the regions of two Mediterranean countries, with a priori similar regional development patterns: Spain and Italy. These countries could be compared in terms of economic-innovation performance and of policy-governance; in both countries regional policies implemented follow different targets with respect to the national ones (Marzucchi and Montresor, 2013). A biannual study covering the period 2004-2012 is carried out, using statistical information from Eurostat. The analysis thus aims to avoid the excessive processing that affects the variables comprising the RIS, and provide results that more closely reflect the reality in the territories under investigation. In this regard, Zabala-Iturriagagoitia et al. (2007) find that said index is strongly conditioned not only by possible errors in the sample, but also by the treatment of the variables and their weights. These should not be established so as to be generally applicable but rather they should be adjusted to the specific characteristics of the regions. The authors recommend the use of official statistics in order to identify similar types of geographical areas.

The research is carried out in two stages. In the first stage, a production function is proposed, which is used to determine the degree to which the regions have been able to maximize their outputs for given inputs. The following analyses are then applied: (1) the intertemporal efficiency of the regions' technological innovation is calculated using an extension of data envelopment analysis (DEA), DEA-Bootstrap; (2) the Malmquist Index (MI) is estimated to make the analysis more dynamic and the results more consistent; and

(3) possible synergies between the levels of efficiency achieved and the geographical location of the regions are examined using analysis of variance (ANOVA).

In the second stage, and for the same time period, multilevel regression is used with a twofold objective: (1) to assess whether the environmental policies adopted by Spain and Italy during these years influence the levels of efficiency achieved by the regions; and (2) to determine whether the countries' innovation efficiency and environmental protection level condition the economic development of these geographical areas. This represents a novel contribution at the regional level to complement the existing literature on the subject and will provide answers to three research questions:

RQ 1. Is there a nexus between the economic development of the regions and the efficiency of the innovation implemented?

RQ 2. Does national environmental policies affect the efficiency of regional innovation?

RQ 3. Do innovation and the environmental performance affect the country's economic development.

In this line of research, there are studies that propose different methodologies to measure environmental innovation in particular industry sectors, as well as national-level analyses (Liao et al., 2020; is and Wendler, 2020; Rosa et al., 2021). Bryden and Gezelius (2017) provide evidence on the design of innovation processes to ensure they are compatible with sustainable development. Others have focused on the nature of inclusive innovation (Lowe and Wolf-Powers, 2018; Peerally et al., 2019). The proposed analysis would address aspects in this area that have not been extensively covered to date. The nature of the chosen sample allows robust results, where the combination of the chosen statistical techniques facilitates the intermingling of the regional and national scope of the proposed research. Regional innovation inputs and outputs are used and linked to national environmental policies and performance indicators. This is a novel contribution to the literature that facilitates the possible detection of analogous patterns between the two countries. The research offers the following theoretical, practical and methodological contributions: (1) the research sheds light on the complex relationship between innovation, sustainable development and regional development, extending the studies of Carayannis et al., 2017; Dolereux and Porto-Gomez, 2017; Berman et al., 2020). (2) practically speaking, the results provide valuable information to the authorities on the measures contributing most to enhancing innovation, and the relative impact on economic development; methodologically, an intertemporal analysis is conducted in order to prevent distortions occurring in the regions from determining the level of efficiency achieved;

The rest of the paper is structured in the following sections. Section 2 provides a review of the literature, establishing the theoretical framework for the analysis. Section 3 describes the methods and data used in the two stages of the research. Section 4 presents the results obtained, as well as a discussion under the current paradigm. Lastly, Section 5 details the main findings of the analysis.

2. Theoretical framework

In the economic literature, technical efficiency has primarily been measured through two approaches, DEA and stochastic frontier analysis. While the former uses linear programming to determine the production frontier that establishes the maximum level of efficiency, the latter applies econometric techniques. Both have proved suitable in a wide variety of fields related to economics and management (Nazarko and Chodakowska, 2017; Sakouvogui, 2020; Yang et al., 2020; Tan et al., 2020). For example, Silva et al. (2017) show that these models provide steady information on the efficiency of banking systems as a whole, but they become divergent at the individual level. Zeng et al. (2021), appling the data-driven text mining approach, review 165 articles for academic journals of innovation efficiency and concluded that the main approaches for investigation are DEA, stochastic frontier analysis and MI. However, when dealing with scenarios involving multiple inputs/outputs and in the presence of non-linearity, DEA has been shown to be superior (Hoff, 2007; Guan and Chen, 2010).

The use of DEA as an instrument to measure the efficiency of productive activities has its origins in the study by Farrell (1957), later being further developed by Charnes, Coopers and Rhodes (1978). This method has been used to quantify the efficiency of R&D projects seeking to generate novel products or introduce improvements in production systems. Innovation is a complex process, the assessment of which requires a certain treatment and flexibility (Tidd and Bessant, 2009). DEA offers this flexibility as it allows multiple aspects and facets of innovation to be combined without having to first establish a form for the production function that defines the process.

The introduction of innovation processes generates progress that can be quantified, making it very useful for shaping future policies that seek to promote best practices (Wang et al., 2016; Namazi and Mohammadi, 2018; Mavi et al., 2019; Wang et al., 2020; Mavi and Mavi, 2021; Yu et al., 2021). DEA have been used to measure efficiency at the national and regional levels. Zemtsov and Kotsemir (2019) compared Russian regions according to their ability to create new technologies efficiently and showed that the efficiency has increased especially in the least developed territories. Min et al. (2020) evaluated the regional efficiencies of technology development and commercialization in South Korea. Their findings indicate that governments should consider policies combining public investment with network building to improve efficiencies and generate technological and commercial value from regional innovation.

Table 1 shows the most relevant studies that have used DEA to measure efficiency and it can be seen a variety of variables are used as inputs/outputs. Each study should be analysed individually; the results are not comparable even if the same variables were used. The level of efficiency achieved by each country/region is estimated on the basis of similarity with the rest of the observations in the sample, relating to a certain production function. However, the conclusions and recommendations could be extrapolated to other economies in which the initial conditions are similar (Brown, 2006).

Regardless of the sample analysed, environmental innovation is shown to be an important factor affecting the efficiency and productivity of innovation processes. As Table 1 shows, some studies have included a second stage in their research to analyse the effects of environmental factors on the level of efficiency achieved. The Tobit model has been widely used due to the limited results of the DEA (Xu et al., 2020; Cavaignac et al., 2020; Chen et al., 2021). Shin et al. (2018) analyze the relationship between sustainability as innovation objective and innovation efficiency of 441 manufacturing companies in Korea, using DEA and Tobit. Their results show that the objective of 'environmental improvement' negatively affects innovation efficiency, while 'safety improvement' positively affects the efficiency. Likewise, partial least squares regression and feasible generalized least squares also allow the researcher to determine the environmental effect on innovation efficiency (Guan and Chen, 2012; Deng et al., 2019).

Table 1. Literature review

Author	Sample	Objective	Methodology	Inputs	Outputs	Link with sustainability/environmental
Wang and Huang (2007)	30 countries	Estimate efficiency and control the environment	DEA BCC input oriented	R&D capital stocks Manpower	Nº of patents Academic publications	Yes
Chen et al. (2011)	24 nations: - 16 European - 4 Asian - 4 American	Compare the relative efficiency of R&D across nations	DEA CCR output oriented	Total R&D manpower R&D expenditure stocks	Patents Scientific Journal articles Royalty and licensing fees	No
Guan and Chen (2012)	22 OECD countries	Two innovation process: knowledge production process and commercialization process (KPP, KCP)	Network two stage DEA Super-efficiency	KPP - Nº of scientists and engineers - R&D expenditure - Prior knowledge KCP - Prior knowledge in commercialization - Labour for non-R&D activities	Connecting KPP y KCP - Nº of patents KPP - Int. scientific papers KCP - Added value of industries - Export of new products	Yes
Lafarga and Balderrama (2015)	32 Mexican regions	Measure the relative technical efficiency	DEA CCR output oriented	Quality graduate programmes Graduate scholarships Research centres Higher education institutes R&D expenditure Researchers Students in science programmes	Patents Scientific publications	No
Zemtsow and Kotsemir (2019)	Russian regions	Measure their ability to efficiently and effectively create new technologies	DEA BCC input oriented	R&D expenditure R&D staff	Patent	No
Deng et al. (2019)	30 Chinese regions	Examine the impact of government competition and environmental regulation on regional innovation performance	DEA super-efficiency	R&D personnel R&D capital	Patent Turnover of new technology market	Yes
Mavi et al. (2019)	OECD counties	Analyze the joint effects of eco-efficiency and eco-innovation	Two-stage DEA	Labor force Energy consumption Land area Intermediates: GDP and GHG emission	Research in R&D High technological export ISO 14001 certificates Electricity production	Yes
Min et al. (2020)	16 South Korea regios	Evaluate the regional efficiencies of technology development and commercialization	Two-stage DEA	R&D expenditure R&D employees Intermediates: Technology output Scientific publications	Rate of technology transfer Export value GDP	No
Lee et al. (2020)	Korea local government	Examines Korea's R&D investment performance at the local government	DEA-SBM DEA- Bootstrap	R&D cost Researchers	Papers Patent	No

In this study, the use of DEA is proposed to assess the level of efficiency of Italian and Spanish regional innovation. Specifically, an extension that circumvents some of its limitations—DEA-Bootstrap[1]—is used, linking the results obtained with environmental measures and regional development. Concerns about ensuring sustainable growth led the European Commission to establish a programme aimed at guaranteeing smart, inclusive development as a way of strengthening the EU economy (Europe 2020 Strategy, European Commission, 2013). The policy components of this strategy revolve around innovation as a driver of sustainable, inclusive growth.

Industrial competitiveness, job creation, labour productivity and efficient resource use must be underpinned by paradigms that facilitate their permanent and dynamic implementation in society, enabling adaptation to change in the environment. Furthermore, R&D and the resulting innovation are key to solving some of the most pressing issues facing society: climate change and clean energy. Su and Moaniba (2017) consider that diverting public funds to areas where innovative activities contribute the most to fighting climate change. In this context, DEA has also been successfully applied to environmental assessment and sustainable development in different spheres of the economy (Olfat et al., 2016; Afzalinejad, 2020; Zhang et al., 2020).

3. Methodology

3.1 Stage 1: Innovation efficiency: Data and methods

The efficiency analysis was carried out using Eurostat regional information for NUTS 2 level, according to the European nomenclature. As a result, 17 Spanish autonomous communities[2] and 21 Italian regions have been evaluated. A panel data sample has been created for each of the countries on a biannual basis, covering the period 2004-2012. It was not possible to carry out a more up-to-date analysis because for certain variables the most recent statistics are from 2012.

The production function required for the efficiency analysis consists of two inputs and two outputs.

Inputs: private R&D expenditure and public R&D expenditure

Outputs: patents and trademark applications

Inputs are lagged to reflect the period of time taken to reach maturity that is characteristic of the innovation process. These variables are frequently used in the literature (Table 1), and include resources for staff as well as other R&D-related expenditure. The outputs represent intellectual property rights (Hauser et al., 2018). Table 2 shows the main statistics of the variables for the territories of the two countries in the period 2004-2012.

Table 2. Descriptive statistics of the variables (2004-2012)

	SPAIN			
	Inputs		Outputs	
	Private R&D expenditure	Public R&D expenditure	Patent	Trademark
Units	% GDP	% GDP	Per million inhabitants	Per million inhabitants
Min	0.04	0.04	1.36	20.71
Max	1.64	0.53	117.55	373.89
Mean	0.52	0.17	27.60	136.90
St.dev	0.39	0.10	26.63	80.52
	ITALY			
Min	0.02	0.01	1.10	2.00
Max	1.45	0.85	217.36	364.57
Mean	0.42	0.15	63.90	92.90
St.dev	0.33	0.16	54.61	71.28

The statistics reveal the first differences between territories. While in Spain the mean R&D expenditure—both private and public—is higher than in Italy, in terms of output Spain only outperforms Italy in trademarks. Regarding the dispersion of the sample, and making a more detailed analysis of the original data, it can be seen that in the Spanish territories the standard deviation is lower in public expenditure and in patents; over 40% of the Italian regions register more private spending, and have an above-average number of patents and trademarks, with this figure being around 35% in the case of Spain. The situation is different with public R&D expenditure, which is above the mean in less than 25% of Italian regions, while in Spain the equivalent figure reaches almost 35%. It can be inferred that the Italian private sector is more aware of the need to innovate, regardless of the effort made by the public sector.

The non-parametric DEA method calculates the relative efficiency of each of the DMUs—in this research, Italian and Spanish regions—characterized by the inputs and outputs listed in Table 2. Charnes et al. (1978) developed the pioneering work of Farrell (1957) under the assumption that production operates on its optimal scale, that is, under constant returns to scale (CRS). In this research, variable returns to scale (VRS) is applied, a model originally proposed by Banker, Charnes and Coopers (1984). The model is output oriented, meaning inefficiency is the result of the suboptimal use of inputs. The efficiency level of each DMU is obtained by solving the following linear programming model:

$$\text{Min } h_0 = \sum_{i=1}^{m} v_i x_{i0} + w_0 \tag{1}$$

s.t.

$$\sum_{r=1}^{s} u_r y_{r0} = 1$$

$$\sum_{r=1}^{s} u_r y_{rj} + \sum_{i=1}^{m} v_i x_{ij} + w_0 \qquad \text{j} = 1, \ldots \text{n}$$

$$u_r, v_i \geq 0 \qquad r = 1, \ldots, s \quad i = 1, \ldots, m$$

where:

h_0: efficiency level
x_{ij}: quantities of input *i* used by the *j*-th unit
y_{rj}: observed quantities of output *r* produced by the *j*-th unit
u_r: input weights
v_i: output weights
w_0: returns to scale

One of the main limitations of DEA is the lack of statistical properties; it is strongly conditioned by the composition of the sample, thus generating biased estimates. DEA-Bootstrap minimizes the contamination of data caused by stochastic noise, providing a broader spectrum to discuss the uncertainty surrounding estimates due to possible sampling variation (Simar and Wilson, 2000). The bias is estimated by resampling, approximating the score obtained with VRS, thus obtaining a result closer to the real frontier and facilitating the construction of confidence intervals. The level of innovation efficiency of the analysed regions has been obtained after 2000 iterations, as recommended by Simar and Wilson (2000). In addition, Shephard's distance has been used, taking the reciprocal value (1/value) as an efficiency score, meaning that it is limited to between 0 and 1, with 1 being the maximum efficiency value. Intertemporal calculation is applied in order to provide stability to the results and facilitate the comparability of regions during the period under analysis (Cruz-Cázares et al., 2013).

The results of the DEA-Bootstrap are taken along with those obtained from the calculation of the MI, which measures the total productivity growth of innovation in each region. If MI > 1, the amount greater than unity represents the productivity improvement relative to the initial period. In addition, two different aspects of growth are quantified: technical efficiency change (EC) and technological change (TC). When EC>1, the region in question has increased its efficiency relative to the rest of the observations in the sample, while if TC<1, it represents technological regress. It could be the case that a region registers technological progress (TC>1) as well as reduced relative efficiency (EC<1).

In turn, Färe et al. (1994) break down EC into two components: pure technical efficiency change (PTEC) and scale efficiency change (SEC). PTEC measures pure technical efficiency in the context of VRS, while SEC measures changes in productivity resulting from changes in the production scale.

Both methodologies have proved suitable for use in this field of research, as demonstrated by the works of Cruz-Cázares et al. (2013), Afzal (2014), Kontolaimou et al. (2016) and Luo et al. (2019), among others.

3.2. Stage 2: Innovation, development and sustainability: Data and method

In line with the research aims, this second stage analyses (1) whether the environmental policies adopted by the central government affect the efficiency of regional innovation, and (2) whether the country's innovation efficiency and environmental sustainability influence its regions' development. Achieving each of these objectives entails the construction of a multilevel regression. This method requires the definition of different levels of variables, in this case, regional and national. In (1), the efficiency obtained by the DEA-Bootstrap is used as the dependent variable, while the independent variables are the following: at the regional level, education[3]; and at national level, the components of the index that reflect the stringency of the environmental policies implemented by the two countries, the Environmental Policy Stringency Index (EPS). In addition, the dependent variable in the regression constructed for (2) is regional GDP per capita, while the independent variables are the following: at regional level, efficiency; and at national level, an index that reflects the degree of environmental sustainability of the country, the Environmental Performance Index (EPI), and its components.

The EPS measures the stringency of the environmental policy implemented by each country, and is constructed to be internationally comparable. Stringency is defined as the degree to which environmental policies put an explicit/implicit price on polluting or environmentally damaging behaviour. Thus, a higher cost on polluting units implies a more stringent environmental policy (higher EPS score). The same interpretation applies to the reduction in emission limits. In the case of subsidies (Feed-in tariffs or Subsidies for R&D), higher values also entail higher EPS scores, because they increase the opportunity cost of pollution and this cost is generally passed on to consumers through taxes.

The index values range from 0 to 6, with 6 denoting the most stringent policies. The index score is based on 14 environmental policy instruments, primarily related to climate and air pollution. These are grouped into two pillars: Market-based policies and Non-market policies. The first includes Taxes, Trading Schemes and Feed-in Tariffs. The second is comprised of Standards and R&D Subsidies (Botta and Kozluk, 2014). Table 3 shows the main statistics of the variables that define the multilevel regression model for the analysis of the first objective of this second stage[4]:

Table 3. Descriptive statistics of the variables (2004-2012). Analysis innovation efficiency-environmental policy

	Regional variables		National variables				
	Upper secondary and post-secondary	Tertiary education	EPS Taxes	EPS Feed-in Tariffs	EPS Trading Schemes	EPS R&D Subsidies	EPS Standards
SPAIN							
Min	12.95	10.20	1.63	2.75	0.10	2.00	1.75
Max	27.10	44.10	2.00	5.50	1.80	2.50	4.50
Mean	20.26	25.33	1.63	2.75	0.10	2.00	1.75
St.dev.	3.06	8.25	2.00	5.50	1.80	2.50	4.50
ITALY							
Min	11.10	7.75	2.13	2.00	0.80	1.50	1.75
Max	49.40	19.40	2.50	2.50	2.30	2.00	4.50
Mean	33.66	12.84	2.30	2.30	1.78	1.90	3.38
St.dev.	10.73	2.51	0.25	0.20	0.55	0.20	1.29

The Environmental Performance Index (EPI) measures environmental trends and progress in 180 countries on the basis of 24 indicators grouped into two categories: environmental health (EH) and ecosystem vitality (EV). While EH is focused on measuring human health protection, EV relates to the protection of natural resources and ecosystem services. In short, the EPI provides a national measure of how close countries are to meeting established environmental policy objectives. It takes values between 0 and 100, with 100 being the ultimate goal for all countries. The statistics for the variables of the second multilevel regression are shown in Table 4.

Table 4. Descriptive statistics of the variables (2004-2012). Analysis economic development- innovation efficiency and environmental sustainability

	SPAIN				
	Regional variables		National variables		
	Constant GDP per capita (in thousands €)	EFF	EPI	EH	EV
Min	14.47	0.09	58.49	96.70	42.12
Max	32.84	0.90	79.79	98.99	67.89
Mean	23.08	0.51	63.73	98.26	48.08
St.dev.	4.58	0.24	8.11	0.95	9.98
	ITALY				
Min	15.70	0.04	68.90	81.46	55.57
Max	38.36	0.85	74.36	100.00	69.63
Mean	26.95	0.45	70.15	96.29	58.61
St.dev.	6.89	0.24	2.12	7.45	5.54

Note: EFF denotes the efficiency results of the DEA-Bootstrap

In order to carry out the multilevel regressions, the data are stratified as shown in Figure 1[5]. The process starts by specifying a null model without covariates, expressed as follows:

$$Y_{ij} = \beta_{0j} + \varepsilon_{ij} \qquad (2)$$

In equation (2), the dependent variable Y_{ij} represents the regional innovation efficiency or the level of development, depending on the objective under analysis; β_{0j} indicates the mean of the response variable corresponding to the year of study, and ε_{ij} the residuals around the mean. The explanatory variables are then introduced in levels. Level 1 will be conditioned by the specific features analysed at regional level:

$$Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + \varepsilon_{ij} \qquad (3)$$

where,

Y_{ij}: dependent variable i in year j
X_{ij}: vector of characteristics of region i in year j
ε_{ij}: vector of residuals

Then, since the relationship between X and Y is conditioned by the different country characteristics for each year, Z_j, level 2 is introduced by modifying the coefficients through the following relationships:

$$\beta_{0j} = \gamma_{00} + \gamma_{01} Z_j + \mu_{0j} \tag{4}$$

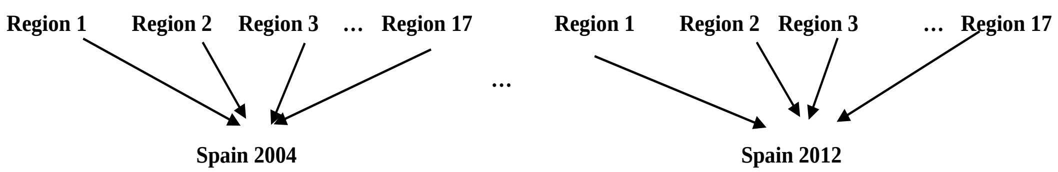
$$\beta_{1j} = \gamma_{01} + \gamma_{11} Z_j + \mu_{1j} \tag{5}$$

Hence, the model to be estimated is defined from the following expression:

$$Y_{ij} = \gamma_{00} + \gamma_{01} Z_j + \gamma_{10} X_{ij} + \gamma_{11} X_{ij} Z_j + (\mu_{0j} + \mu_{1j} X_{ij} + \varepsilon_{ij}) \tag{6}$$

with Z_j being the vector of country characteristics in year j and μ the new residuals

Figure 1. Spanish multilevel structure



An additive approach is used to calculate the results (Dronkers and Robert, 2008). This entails first estimating model (2), in which no independent variable is included, in order to decompose the variance of the results at different levels. The explanatory variables represented in model (6) are then introduced into the initial equation. There are a number of studies in the literature that apply this method to innovation-related issues (Balka et al., 2013).

4. Results and discussion

The DEA-Bootstrap model is based on two production functions, one for the Italian regions and the other for the Spanish regions. The two samples are different but fulfil the conditions of homogeneity between the observations therein. The results represent the average level of efficiency of each region. In no case they reflect the volume of innovation performed, only whether or not the regions have been able to make appropriate use of the available resources to achieve the maximum output. Table 5 shows the results obtained during the period analysed for each of the territories, specifically the mean (EFF mean), the standard deviation (EFF Std. Dev.) and the number of times that the region in question has been efficient (Nº EFF =1).

Table 5. Efficiency scores of the intertemporal DEA-Bootstrap (2004-2012)

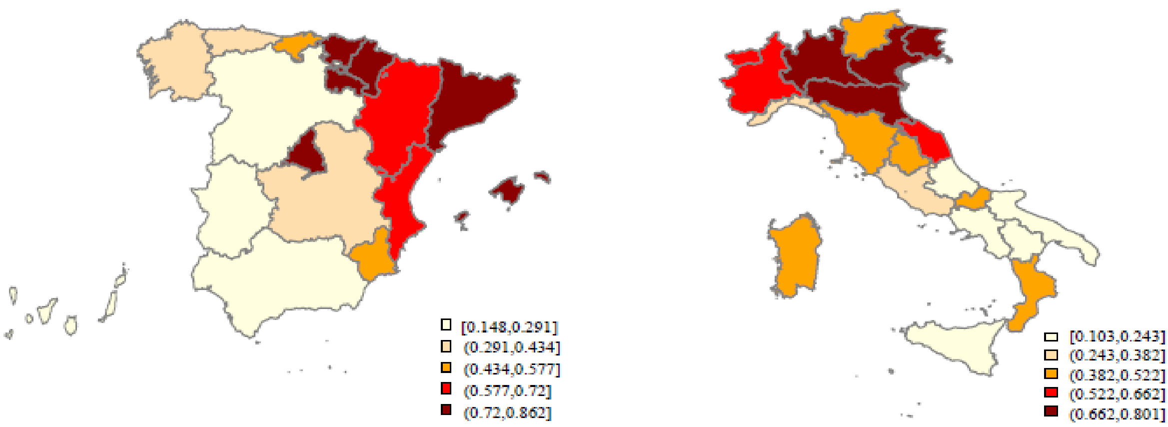
SPAIN	EFF mean	EFF Std Dev	Nº EFF =1	ITALY	EFF mean	EFF Std Dev	Nº EFF =1
Northwest				**Northwest**			
Galicia	0.323	0.074	0	Piemonte	0.602	0.076	0
Principado de Asturias	0.317	0.111	0	Valle d'Aosta	0.535	0.179	0
Cantabria	0.479	0.162	0	Liguria	0.344	0.056	0
				Lombardia	0.801	0.044	1
Northeast				**Northeast**			
País Vasco	0.741	0.043	1	Provincia Autonoma di Bolzano	0.744	0.065	4
Comunidad Foral de Navarra	0.764	0.047	2	Provincia Autonoma di Trento	0.467	0.174	0
La Rioja	0.769	0.093	3	Veneto	0.753	0.051	1
Aragón	0.662	0.117	0	Friuli-Venezia Giulia	0.743	0.084	1
Cataluña	0.862	0.049	1	Emilia-Romagna	0.758	0.062	1
Centre-East				**Centre**			
Comunidad de Madrid	0.729	0.067	0	Toscana	0.479	0.054	0
Castilla y León	0.261	0.023	0	Umbria	0.518	0.044	0
Castilla-la Mancha	0.314	0.061	0	Marche	0.562	0.095	0
Extremadura	0.148	0.046	0	Lazio	0.257	0.009	0
Comunidad Valenciana	0.670	0.040	0	Abruzzo	0.236	0.029	0
				Molise	0.406	0.242	1
South and Islands				**South and Islands**			
Illes Balears	0.738	0.048	4	Campania	0.103	0.015	0
Andalucía	0.242	0.036	0	Puglia	0.199	0.020	0
Región de Murcia	0.447	0.080	0	Basilicata	0.138	0.077	0
Canarias	0.247	0.049	0	Calabria	0.448	0.203	0
				Sicilia	0.110	0.049	0
				Sardegna	0.406	0.076	0

The level of efficiency achieved by each region is comparable to that of the rest of the DMUs in its own country, but in no case can it be compared with regions in the other country. Although the same inputs/outputs have been used, two different production frontiers have been constructed, and the efficiency levels of each one have been obtained on the basis of similarity with the DMUs in their own sample (Brown, 2016).

By geographical area, it is the north-eastern regions that stand out in both countries. These are areas with high levels of industrial development, and which have made better use of the resources targeted at innovation than other regions have, such as those in the south

(Figure 1). In Spain, under very different circumstances, Cataluña, Comunidad de Madrid, and Illes Balears each scored higher than 0.7; in other words, given their available inputs, these regions could increase their outputs by 30%. According to the latest data from the Spanish National Institute of Statistics, Cataluña and Comunidad de Madrid are the territories that allocate the most resources to R&D. These autonomous communities are positioned third and fourth respectively in terms of the number of companies dedicated to innovation, surpassed only by País Vasco and Comunidad Valenciana. Conversely, Illes Balears is one of the regions that allocates the fewest resources to R&D. This fact can be interpreted in two different ways: since the inputs are so limited, not much effort is required to get the most out of them; or, on the contrary, although the amount allocated is very small, the inputs are managed so well that in 4 out of the 5 years analysed, the maximum level of efficiency has been achieved.

Figure 1. Regional efficiency scores. DEA-Bootstrap (2004-2012)[6]



In Italy, on the other hand, Lombardia is the highest-scoring region. It is a highly populated territory—the inhabitants of this region account for one-sixth of Italy's total population—and has a GDP per capita that far exceeds the national average. Its focus on innovation, along with the fact that it is a very industrial area, has allowed it to develop novel production processes that ensure it leads the way in the country.

The MI determines the productivity growth of the DMUs during the period 2004-2012, irrespective of their efficiency score (Table 6). Thus, for example, in the "South and Islands" area of Italy, where DEA-Bootstrap reported very low levels of efficiency, the MI indicates high productivity growth, reaching 31.6% in Basilicata. In the northeast, on the other hand, the decline in productivity ranges between 31.7% (Provincia Autonoma di Trento) and 1.4% (Friuli-Venezia Giulia). Something similar happens in Spain, where Andalusia, with a level of inefficiency of 75.8% in the period analysed, registers an increase in productivity of 4.9%.

Changes in productivity can be caused by EC and/or TC; for the sake of brevity, the result for EC has been omitted, replacing it with its two components PTEC and SEC[7]. Continuing with Andalusia, the growth of 4.9% was due exclusively to an improvement in its technical efficiency, that is, to better use of the available technology (15.1%, PTEC) and, to a lesser extent, to progress made in scale efficiency (2.1%, SEC), bringing its R&D activity closer to its optimum size.

Table 6. Efficiency scores of the Malmquist Index (2004-2012)

SPAIN	MI	TC	PTEC	SEC	ITALY	MI	TC	PTEC	SEC
Northwest					**Northwest**				
Galicia	0.995	0.826	1.151	1.046	Piemonte	0.885	0.780	0.957	1.185
Principado de Asturias	0.818	0.895	1.126	0.812	Valle d'Aosta	1.071	0.958	1.074	1.040
Cantabria	0.973	0.903	1.134	0.950	Liguria	0.947	0.947	1.015	0.985
					Lombardia	1.019	0.965	1	1.056
Northeast					**Northeast**				
País Vasco	0.846	0.846	1	1	Provincia Autonoma di Bolzano	0.904	0.904	1	1
Comunidad Foral de Navarra	0.789	0.827	0.962	0.992	Provincia Autonoma di Trento	0.683	0.947	0.680	1.060
La Rioja	0.782	0.848	1	0.922	Veneto	0.891	0.921	1	0.968
Aragón	1.087	0.914	1.180	1.008	Friuli-Venezia Giulia	0.986	0.895	1	1.102
Cataluña	0.865	0.841	1.000	1.029	Emilia-Romagna	0.866	0.839	0.988	1.044
Centre-East					**Centre-East**				
Comunidad de Madrid	1.001	0.894	1.064	1.052	Toscana	0.885	0.917	0.983	0.981
Castilla y León	0.852	0.804	1.109	0.955	Umbria	0.966	0.999	0.976	0.991
Castilla-la Mancha	0.931	0.890	1.107	0.945	Marche	0.991	0.879	1.096	1.028
Extremadura	0.836	1.005	1.028	0.810	Lazio	1.059	1.118	0.952	0.995
Comunidad Valenciana	0.939	0.852	1.041	1.058	Abruzzo	1.094	0.998	1.072	1.022
					Molise	1.053	1.053	1	1
South and Islands					**South and Islands**				
Illes Balears	0.947	0.947	1	1	Campania	1.184	1.083	1.008	1.084
Andalucía	1.049	0.893	1.151	1.021	Puglia	1.049	1.092	0.950	1.012
Región de Murcia	0.923	0.844	1.166	0.937	Basilicata	1.316	1.059	0.927	1.341
Canarias (ES)	0.959	0.931	1.091	0.944	Calabria	1.131	1.115	1	1.015
					Sicilia	0.764	1.071	0.925	0.771
					Sardegna	1.009	1.041	0.969	1

In Spain, the decline in productivity has mostly been due to the poorer technological progress (TC), although almost all communities have made better use of their technology (PTEC), a result less widespread in Italy. In the Italian region "South and Islands" the increase in the MI is attributed to technological advances, ranging from 4.1% for Sardegna to 11.5% for Calabria. All of these areas, except Sicily, have come closer to their optimum size.

An ANOVA is then performed to determine whether there are significant differences in efficiency levels according to geographical location. The null hypothesis is rejected for both Spain and Italy, confirming that the efficiency levels achieved in the different geographical areas are not homogeneous[8]. However, whereas in Italy the average level of efficiency ranges between 0.234 for "South and Islands" and 0.693 for "Northwest", with three groups being identified, in Spain these figures range between 0.373 and 0.760 for "Northwest" and "Northeast", respectively (Table 7).

Table 7. Groups resulting from the ANOVA

ITALY	**N**	**1**	**2**	**3**
South and Islands	6	0.234		
Centre-East	6	0.410	0.410	
Northeast	4		0.571	0.571
Northwest	5			0.693
SPAIN		**1**		**2**
South and Islands	4	0.419		0.419
Centre-East	5	0.424		0.424
Northeast	5	0.760		
Northwest	3			0.373

Note: Tukey-Kramer in Italy. Games-Howell in Spain. Significance level 0.05.

In line with Chen et al (2020), the results show that there are differences in the innovation efficiency of the provinces. The highest levels of efficiency are achieved in the more industrialised areas of both countries. However, there is no common pattern in terms of productivity changes over the period analysed (RQ 1).

The next stage of the research aims to analyse whether national environmental policies have affected the level of regional efficiency. As explained in Section 3, a multilevel regression model is used, taking innovation efficiency as the dependent variable, and education and EPS components as independent variables. Given that the results of innovation are seen a year or two after the efforts made in R&D, it was decided that the environmental policies that might affect them should be taken as an average of the scores obtained during the previous two years. A similar criterion was applied for education. These policies have a direct impact on companies' cost structure as they must incorporate the expenses incurred as a result of having to reduce pollution. As an immediate reaction, companies may opt to move their production to countries with laxer environmental regulation (ER), thereby gaining comparative advantages through cost savings. However, the opposite interpretation may apply: these policies could be perceived positively because they encourage companies to introduce novel, higher quality products that cover the higher costs caused by the ER. The results obtained from the application of the multilevel regressions show that in both Spain and Italy environmental policies and education positively affect innovation efficiency (Table 8).

Table 8. Estimates of innovation efficiency

	SPAIN	**ITALY**
Upper secondary/post-secondary	0.047^{***}	0.020^{***}
Tertiary education	0.015^{***}	
EPS Taxes	0.241^{**}	4.463^{***}
EPS Feed-in Tariff	0.104^{***}	21.747^{***}
EPS Trade		
EPS R&D Subsidies	0.100	20.554^{***}
EPS Non-market standards		4.526^{***}

Dependent variable: Efficiency Bootstrap, EFF
*** p-value < 0.01, ** p-value < 0.05, *p-value < 0.1

Again, the coefficients for the two countries are not comparable because their specific characteristics have prevented the use of exactly the same variables. Although stringency translates into higher costs, this does not lead to a drop in efficiency levels. The subsidy instruments (Feed-in Tariff and EPS R&D Subsidies) have a very positive impact in both countries (21.747 and 20.554 in Italy, respectively, and 0.104 in Spain).

In the same area, Porter (1991) and Porter and van der Linde (1995) analyse the impact of ER on business investment decisions, confirming that when environmental policies are properly designed, they improve business competitiveness and foster innovation, promoting technological change. However, others such as Palmer et al. (1995) and Walley and Whitehead (1994) criticize the lack of evidence on how companies offset environmental costs to prevent loss of competitiveness. Subsequent studies carried out have concluded that ER increases R&D spending, and even positively influences patent applications and factor productivity (Morales-Lage et al., 2016[9]; Hille et al., 2020). The results obtained in the study underpin these conclusions by providing evidence of the positive effects of ER on the regional efficiency of innovation processes (RQ 2).

The final issue analysed is whether the country's efficiency and level of environmental sustainability affects the development of the regions. The dependent variable representing regional development is the GDP per capita of the 17 Spanish and 21 Italian territories, sourced from Eurostat. It has been deflated using the Consumer Price Index (CPI), to avoid the effect of price changes during the period of study (Table 9). Three models have been estimated in order to analyse each of the EPI components in isolation.

Table 9. Estimates of economic development

	SPAIN			ITALY		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
EFF	11.968***	11.479***	11.947***	18.379***	18.337***	18.362***
EPI	-1.164***			-0.489**		
EH		3.561***			0.140**	
EV			-0.947***			-0.188**

Dependent variable: GDP per capita constant prices
*** p-value < 0.01, ** p-value < 0.05, *p-value < 0.1

All the models presented in Table 9 converge towards the same results, indicating the major importance of innovation efficiency for regional development. In addition, the negative relationship between EPI and GDP per capita is confirmed; applying a disaggregated analysis reveals that this sign is due to EV, which is significant and negative in both countries, albeit with very low weight (-0.947 and -0.188 in Spain and Italy, respectively). The EH component is found to be significant and positive in the regions of both countries. This allows to answer to RQ 3, indicating that innovation and *national environmental policies positively affect the country's economic development.*

All territories are adopting measures to reduce pollution and improve the quality of life of society in a sustainable way. Nevertheless, not all the measures have translated equally into economic development. It has not yet been possible to integrate EV into the economy of the population in a positive way, perhaps because of the higher associated cost of goods and services, which reduces purchasing power. Despite this, and in line with the conclusions of Roy and Goll (2014), both the private and public sectors must be held accountable for their actions related to pollution control, as well their management of natural and human resources, all of which pose a social and economic challenge. It is about providing continuity to the economic theory of sustainable growth. This idea, which dates back to the 1960s when the environmental conservation movement was born, holds that economic growth has to be based on a sustainable use of the available natural resources (García-Sánchez et al., 2015). Recently Ferreira et al (2020) confirmed that innovation can contribute to countries' sustainable economic growth and effectively respon to climatic change.

5. Discussion, implications and conclusions

5.1 Discussion of findings

This research provides evidence of the relationship between innovation, environmental policies and sustainability at the regional level. To that end, a two-stage analysis was performed. First, an intertemporal study was conducted to quantify the level of efficiency of the Spanish and Italian regions in the period 2004-2012, as well as the corresponding productivity growth. Second, the analysis determined the effect on efficiency of the stringency of environmental policies adopted at the national level by each country, as well as the possible relationship between economic development, and environmental sustainability and efficiency. From a methodological point of view, the DEA-Bootstrap has been used to overcome the limitations of traditional DEA analysis, obtaining more accurate efficiency results. The 2000 interactions avoid the effect that could be caused by the presence of outliers. In addition, multilevel regression makes it easier to place the regional study at a higher level, introducing national factors that condition innovation and development. This methodology solves the problems of correlation between observations, allows to determine the direct effect of individual and group explanatory variables, as well as possible interactions between levels.

The results reveal a common pattern of behaviour in the north-eastern regions of both Spain and Italy (RQ 1). On average, they are the ones that make the best use of R&D resources, securing patents and trademarks that help ensure growth in these areas. These are more industrialised areas that need to continuously introduce new innovation-oriented technologies that favour the international competitiveness of their products. This study is driven by the need for a study focusing specifically on the actions carried out in Lombardia and Comunidad de Madrid, as they achieve a much higher level of efficiency than the other regions in their respective geographical areas.

The second stage of the research reveals that the stringency of environmental policies, far from damaging innovation efficiency, have positive effects. There should thus be more emphasis on stringent policies in regions with lower efficiency levels (RQ 2). This is a way to ensure the development of the regions; both efficiency and EH significantly affect the GDP per capita of the Spanish and Italian territories (RQ 3).

Currently, the fight against climate change is bringing about changes at all levels, in both the private and public spheres. Innovation cannot be analysed exclusively from a technology- and market-oriented perspective; it should form an integral part of a sustainability approach. It needs to be addressed and developed in an interdisciplinary context, alongside social and environmental aspects, as well as technological and scientific elements.

R&D and the resulting innovation are very useful tools, together with industrial policies, for ensuring the ecological growth of nations. Weaker economies should focus their efforts on adapting technologies that have already been developed. As stated by the European Commission, the major challenge today is to be able to properly combine innovation and environmental policies, promoting strategies that foster the adoption and diffusion of new technologies compatible with the green growth of the economy. This represents a great challenge, since authors such as Ramanathan et al. (2018) have demonstrated that innovation capabilities significantly influence financial performance of firms if firms feel that the environmental regulations they face are flexible and offer more freedom in meeting the requirements of regulations. According to Hakimi and Inglesi-Lotz (2019) show that there is a positive response from climate change to innovation. The level of growth and R&D expenditure exert a positive effect on innovation process for both aggregate and disaggregate analysis.

5.2 Theoretical, practical and methodological implications

The findings allow to put forward the following theoretical and practical implications. First, the study adds to the literature on regional development (Carayannis et al., 2017; Dolereux and Porto-Gomez, 2017; Berman et al., 2020), by shedding light on the complex relationship between innovation, sustainable development and regional economic development. The results show great differences between the territories of the two countries analysed, confirming the need to establish differentiated policies that encourage the adoption of innovation practices in regions whose efficiency scores have shown a lack of rigour in the use of their resources, i.e. south Italian and Spanish regions. Furthermore, it has been shown that the stringency of environmental policies positively affects innovation efficiency, with a positive relationship found between development, innovation and environmental sustainability. These results are in line with other works in the literature, where environmental strigency has a positive effect on R&D expenditure, increase the number of patent application and productivity growth (Albrizio et al, 2017; Martínez-Zarzoso et al, 2019; Hille and Möbius, 2019). The comparison between Italian and Spanish regions allows to appreciate the possible existence of a common pattern of behaviour that could serve to guide the strategies to be adopted by the most backward regions. In addition, the conclusions obtained can be extended to other countries whose regional contribution to the overall national computation is comparable to the countries analysed.

Second, from a practical perspective, the results provide valuable information to the authorities on the measures contributing most to enhancing innovation, and the relative impact on economic development; this can drive choices, investments, projects management and so forth. Third, from a methodological perspective, the research adopts the DEA approach, namely a non-parametric methodology that enables a relative efficiency evaluation of decision making units (DMUs) charactering by multiple input and output measures of performance. The extension proposed in this research, DEA-Bootstrap, offers information on estimates’ uncertainty, according to which it can be determined whether differences between two or more estimates are statistically significant. In turn, MI determines whether there are productivity improvements amongst regions over time, and its components assign the origin of these enhancements. The second part proposes the use of multilevel regressions which allows to analyse the national context. The reason for using parametric techniques is because they summarise the impact of external factors over the efficiency in a single coefficient.

5.3 Limitations and future lines of research

The research carried out is not free from limitations, which will be addressed in future studies. The regional information available in Eurostat imposes certain limits on the aspects that can be analysed; for example, it is not possible to differentiate between process and product innovation. These issues would provide more information and could enrich the conclusions. For this reason, the aim is to carry out an efficiency analysis that particularly focuses on specific sectors of the economy. The results will provide more specific information on the regional situation, as well as the concrete effects of environmental policies and their impact on regions' development.

Furthermore, this analysis should be extended to other European countries, such as Germany, France and England, in order to detect whether their possible national analogies translate into similar regional developments in terms of innovation and environmental sustainability. It is proposed to use other environmental variables, such as greenhouse gas emissions, to reveal the authorities' involvement in international climate change agreements.

Funding: *This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.*

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Table1A. Results Anova. Spain

	Statistician	Df1	Df2	Pvalue
Welch	12.604	3	5.923	0.006

Table 2A. Results Anova. Italy

	SumSq	Df	MeanSq	Fvalue	Pvalue
inter-group	0.642	3	0.214	9.514	0.001
intra-group	0.382	17	0.022		
Total	1.024	20			

[1] The limitations of DEA mainly stem from the sensitivity of the results to variability in the sample, the quality of data that make up the sample, and the presence of atypical values (Herrera and Pang, 2005). Simar and Wilson (2000 and 2008) propose the use of the bootstrap to deal with some of these issues.

[2] Due to a substantial lack of data for Ceuta and Melilla, these two autonomous cities have been eliminated from the analysis.

[3] Population aged 25-64 with upper secondary and post-secondary education and population aged 25-64 with tertiary education.

[4] The efficiency level statistics, the dependent variable, are shown in Table 4.

[5] The information for the multilevel regression for Italy has been similarly stratified.

[6] It has not been possible to graphically separate the Provincia Autonoma di Bolzano and the Provincia Autonoma di Trento.

[7] This decision was made because EC = PTEC x SEC, with the analysis of its components being more precise.

[8] See Table 1A and Table 2A. Since the assumption of homoscedasticity has not been met in the case of Spain, the Brown-Forsythe test is used instead of the F-test.

[9] Morales-Lage et al. (2016) carry out a review of the studies that analyse the impact of ER on innovation in specific sectors of the economy