Authors' version

National systems of innovation in the Eurozone: Policy implications for Spain

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Abstract

This paper aims to understand which innovation inputs are more strongly related to innovation outputs in the Eurozone, and to derive policy implication for the Spanish convergence with Eurozone top players in terms of innovation. Drawing from the Global Innovation Index input-output framework we developed an alternative longitudinal index. The resulting country scores were used to construct a panel dataset composed of the 19 Eurozone members during the period 2013-2018, which were analysed through a series of multiple regression techniques. Results suggest a strong and positive influence of Business Sophistication on innovation outputs in Eurozone countries, derived mainly from the capacity of domestic firms to absorb knowledge. Possible implications for Spain could be derived from this fact, such as, for instance, encouraging inward foreign direct investment. Future research is needed to analyse the differentiated effects of such encouragement, as well as other surprising results of our study.

JEL Codes: D83; O30; O33; O38.

Keywords: Innovation; Eurozone; panel data; Spain.

Resumen

Este artículo tiene como objetivo comprender qué inputs de innovación están más fuertemente relacionados con los outputs innovadores en la zona euro y derivar implicaciones políticas para la convergencia española con los principales países de la zona euro en términos de innovación. A partir del marco de input-output del Índice Global de Innovación, desarrollamos un índice longitudinal alternativo. Las puntuaciones resultantes se utilizaron para construir un conjunto de datos de panel compuesto por los 19 miembros de la zona euro durante el período 2013-2018, que se analizaron mediante una serie de técnicas de regresión múltiple. Los resultados sugieren una fuerte y positiva influencia de la sofisticación empresarial en los resultados de innovación en la zona euro, derivados principalmente de la capacidad de las empresas nacionales para absorber el conocimiento. Las posibles implicaciones para España podrían derivarse de este hecho, como, por ejemplo, un estímulo a la inversión extranjera directa. Se necesita investigación futura para analizar los efectos diferenciados de tal estímulo, así como para otros resultados sorprendentes de nuestro estudio.

JEL Codes: D83; O30; O33; O38.

Palabras clave: Datos de panel; España; innovación; zona euro.

1. INTRODUCTION

National Systems of Innovation (NSI) are recognized as cornerstones for countries' international competitiveness (Fagerberg & Srholec, 2008; Freeman, 1987, 1995; Furman et al., 2002; Lundvall, 1992; Nelson, 1993), broadly defined as "all important economic, social, political, organisational, institutional, and other factors that influence the development, diffusion, and use of innovations" (Edquist, 2006: 182). This definition highlights the essentially systemic nature of innovation, involving a nation's organisations and state in the innovation process.

In order to improve a country's innovative capacities, policy decision makers must be able to understand which factors are driving innovation in their economies (Kuhlman et al., 2017). Hence, it becomes necessary to find ways of measuring the investment made in NSI and the resulting outcomes of such investments (Borrás & Laatsit, 2019). To that end, several major international organisations have developed frameworks to analyse the innovation readiness of countries, such as the European Innovation Scoreboard (European Commission, 2018), the Nordic Innovation Annual Report (Nordic Innovation, 2018), the OECD Science, Technology and Innovation Scoreboard (STI, OECD, 2017) or the Global Innovation Index (GII, Cornell University et al., 2018).

Recent literature on Spanish innovation using a national system of innovation framework is rather inexistent. The main sources of innovation indicators used are the Survey of Business Strategies (ESEE) (Manzaneque et al., 2018; Radicic & Balavac, 2019; Santos Arteaga et al., 2019; Ubeda & Pérez-Hernández, 2017), the PITEC Innovation Technology Panel (Alarcón et al., 2019), European Commission's Community Innovation Survey (Mate-Sanchez-Val & Harris, 2014), and private databases (Leydesdorff & Porto-Gomez, 2019).

Therefore, to address this gap in empirical research, we rely on the framework provided by the GII due to its clear distinction between innovation inputs and outputs, based on more than 80 comparable indicators (Cornell University et al., 2018). Besides being developed by major international organisations, the index is audited by European Commission's Joint Research Centre (EC-JRC) to attest its statistical validity. Hence, it may be used as a leading reference for public policy makers, business executives, as well as for researchers (Sohn et al., 2016).

Nonetheless, the GII methodology gives rise to a number of difficulties if one aims to compare countries' scores over time (Cornell University et al., 2018). The major concern in this respect is that reports are conducted to assess innovation readiness of countries in a given year, lacking a longitudinal framework to track changes over time. One of the GII's aims is to include as many middle and low-income economies as possible (Cornell University et al., 2018), which, depending on the availability of data, results in different sample sizes throughout the years. To address this, and other methodological limitations of the GII when conducting longitudinal analysis, we developed a panel dataset based on the GII framework and followed its methodology to the extent possible.

Following the theoretical base of the input-output framework (Godin, 2007) and the GII framework, we intend to answer the questions: Which innovation inputs are more strongly related to innovation outputs in the Eurozone? And, how can Spain improve its national system of innovation to converge with Eurozone top innovators? To that end, we developed a panel dataset based on the GII framework, composed of 92 countries during the period 2013-2018. Then, we used the resulting scores of the 19 Eurozone members to analyse the relationships between innovation inputs and outputs through multiple regression techniques, in order to understand which inputs have a greater contribution to innovation outputs. Lastly, we evaluate the performance of Spanish innovation by comparison with the Eurozone and derive policy implications.

The decision to use the Spanish context was based on two major observations. First, Spain is currently the fourth largest economy in the Eurozone, whose GDP in 2018, according to the World Bank, represented more than 10% of Eurozone's GDP. As such, not only is the country dependent on decisions coming from the group, but the Eurozone is also dependent on decisions coming from a large country such as Spain. Second, the Spanish economy ranks 28th in the 2018 Global Innovation Index out of 126 countries. However, it depicts the country's business sophistication pillar as Spain's greatest weakness, ranking among Eurozone's bottom three in this pillar. Therefore, we consider necessary to understand the main drivers of innovation outputs in the Eurozone to derive policy implication directed at improving Spain's national system of innovation.

The remainder of this paper is structured as follows. In section 2, we put forward our own development of a longitudinal GII framework. Next, in section 3, we propose a conceptual model to answer the research question and, following the literature review, we develop the hypothesis. The methodology used constitutes section 4. In section 5, results are presented and discussed. In section 6, we elaborate on Iberian performance over time by comparing it with the Eurozone and derive implications based on previous results. Lastly, section 7 lay down the conclusions, including the study's limitations and directions for future research.

2. THE GLOBAL INNOVATION INDEX (GII) AND PROPOSED LONGITUDINAL DEVELOPMENT

As mentioned before, we make use of the GII framework to analyse which innovation inputs are more strongly related to innovation outputs. The GII was launched in 2007 by INSEAD to shed light on the measurement of innovation readiness of countries and to find means of generating meaningful comparisons (Dutta et al., 2007), helping business leaders and public policymakers to understand the reasons of a nation's relative performance (Dutta, 2009).

Nevertheless, the use of GII data for longitudinal studies is discouraged due to several methodological issues (Cornell University et al., 2018). First, the GII is compiled on an annual basis, providing a cross-country innovation performance assessment, hence presenting the characteristics of a cross-sectional study (i.e. several individuals at one moment in time) rather than a longitudinal one (several individuals tracked through several periods of time). As such, methodological changes from one year to the next distort the results in a panel study. Second, since 2007, the framework has undergone several changes in its structure, with the addition or removal of pillars, sub-pillars, and individual indicators. Third, from one year to the next, several countries are added or removed, based on the availability of indicators. Fourth, the gathering of indicators over time suffer from changes in definitions and methodologies. Fifth, collected data undergoes a process of normalization, thus rendering it incomparable in the presence of changes from one year to the next. To address these limitations, in the next section we develop a longitudinal version of the GII.

2.1 Period selection

The GII has unstandardized data available in its website only since the 2013 report. Consequently, we have considered the period from 2013 to 2018.

2.2 Indicator selection and collection

As mentioned above, some indicators were added or removed throughout the period analysed. As such, aiming to maximise the total number of indicators, we have taken the following steps: (1) we dropped seven indicators which appeared only in 2013 and 2014 (Press freedom, Gross tertiary outbound enrolment, Electricity consumption, Market access for non-agricultural exports, GMAT mean scores, GMAT test takers, and Daily newspaper circulation), and one that only appeared in 2018 (Mobile app creation); (2) we also set aside two indicators for which we had only three consecutive years of data, due to lack of availability of data at the original source (Global R&D companies (average expenditure, top 3), and Patent families filled in at least two/three offices); (3) for two indicators, the last year was left blank due to a change in their collection methodology and lack of available data at the original source (High-tech and medium high-tech output, and Printing, publications and other media output). For the same reason, one indicator was left with the last two years blank (Wikipedia monthly edits) and one indicator was left with the first year blank (Entertainment and media market); (4) two other indicators were left with the last year blank due to their removal of the 2018 report (Ease of paying taxes, and Video uploads on YouTube). The complete list of indicators used, as well as their definitions, sources, and time-series, is shown in Table A1 in appendix.

2.3 Country selection

Since the number of countries present in GII reports varies from one year to the next, we have first selected those which are present in every report in the period of 2013 to 2018. Next, following Cornell University et al. (2018), we dropped countries which had more than 33% of missing values of the 53 input indicators (average for the period), and more than 33% of missing values of the 27 output indicators (average for the period). As such, we have obtained a sample of 92 countries (Table A2 in appendix) which, according to the World Bank's World Development Indicators, in 2018 accounted for 82.5% of the world's GDP (PPP $) and about 78.0% of the world's population.

2.4 Identification and treatment of series with outliers

Following the same methodology of Cornell University et al. (2018), we have identified a total of 35 indicators with outliers that could polarize results; 34 out of the 57 hard data indicators and 1 out of the 18 composite indicators. The identification and treatment of series with outliers was done through the following steps: (1) first, we have used the criterion of absolute skewness greater than 2.25, or a kurtosis greater than 3.5 to identify problematic indicators; (2) then, series with one to five outliers (indicator 212) were winsorized, where the values distorting the indicator were assigned the next highest value, up to where the previous criterion was met (only one value was adjusted, from 64.997 to 64); (3) series with more than five outliers were multiplied by a given factor *f* (both positive and negative powers of 10 were used) and transformed into their natural logarithms according to the following formulas:

For 'goods' indicators
$$\ln\left[\frac{(\max * f - 1)(\text{economy value} - \min)}{\max - \min} + 1\right]$$

For 'bads' indicators
$$\ln\left[\frac{(\max * f - 1)(\max - \text{economy value})}{\max - \min} + 1\right]$$

The first equation represents the formula used on indicators for which higher values indicate better outcomes ("goods"), such as Government Effectiveness, and the second equation was used on indicators for which higher values indicate worse outcomes ("bads"), such as the Cost of Redundancy Dismissal, with "min" and "max" being the minimum and maximum values for each series of indicators. For indicators 534 and 634, although the log transformation did lower their skewness and kurtosis values, it was not sufficient to meet the criterion (skewness 2.28 and kurtosis 34.33, and skewness 2.16 and kurtosis 43.21, respectively). Hence, we have decided to keep the transformed indicators avoiding further transformations.

2.5 Normalisation, aggregation, and indices construction

According to the methodology of Cornell University et al. (2018), all 80 indicators were normalised into the [0,100] range, with higher score representing better outcomes. We used the min-max method to normalise indicators, where the min and max values were given by the minimum and maximum indicator sample value respectively, except for survey data and some indices, for which original ranges were kept as minimum and maximum values (for instance, [-2.5, 2.5] for the Worldwide Governance Indicators; [1, 7] for the World Economic Forum Executive Opinion Survey questions; and [1, 5] for the Logistics Performance Index). Thus, we have applied the following formulas for "goods" and "bads" indicators:

'goods' $$\frac{\text{economy value} - \text{min}}{\text{max} - \text{min}} * 100$$

'bads' $$\frac{\text{max} - \text{economy value}}{\text{max} - \text{min}} * 100$$

Once normalised, indicators were aggregated at the sub-pillar level according to the weights proposed in Cornell University et al. (2018). Pillars were then created by a simple average of their respective sub-pillars, and the input and output sub-indices were created by a simple average of their respective pillars. Lastly, the overall index was created by a simple average of input and output sub-indices, while the efficiency index is the ratio of the output sub-index over the input sub-index.

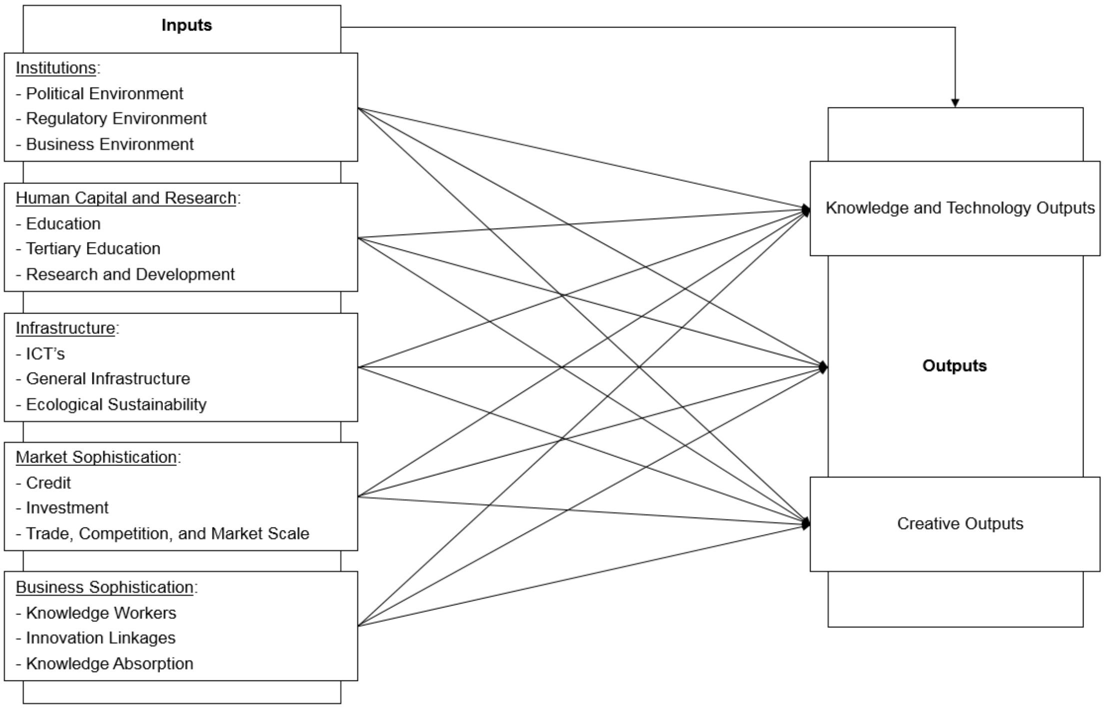
From this point onwards, all analyses are based on the longitudinal GII developed above, thus the terms LGII and GII are interchangeable.

3. Conceptual Model, Literature Review and Hypothesis

In this section we propose a conceptual model to study which innovation inputs are more strongly related to innovation outputs. Figure 1 shows the proposed conceptual model, in which arrows represent the hypothesis developed below.

The NSI approach was introduced in the 1980s (see Freeman, 1995; Lundvall, 2007) and, since then, numerous studies were developed in an attempt to measure and compare such systems (e.g. Erciş & Ünalan, 2016; Fernandez Donoso, 2017; Furman et al., 2002; Kwon et al., 2016; Niosi et al., 1993; Patel & Pavitt, 1994; Porter & Stern, 1999; Sohn et al., 2016). The impact of NSI on international competitiveness (Furman et al., 2002; Nelson, 1993) led to the creation and widespread use of various indicators by major international organizations, such as the EIS (European Commission, 2018), the NIAR (Nordic Innovation, 2018), the OECD STI Scoreboard (OECD, 2017) and the GII (Cornell University et al., 2018). Such indicators are often developed to characterise and compare countries' NSI, lacking the distinction between inputs and outcomes of such systems (Edquist et al., 2018), thus impeding the assessment of innovation efficiency, which, according to some authors (e.g. Cruz-Cázares et al., 2013; Edquist et al., 2018), is the best measure of innovation.

Figure 1: Conceptual model



Source: Own elaboration

The notion that innovation inputs are transformed into innovation outputs is a very straightforward one (for a review, see Godin, 2007). Cornell University et al. (2018) describe a positive relationship between innovation inputs and outputs in every income group. Consequently, we propose the following hypothesis.

H1: Innovation inputs have a positive relationship with innovation outputs.

Following North's (1990: 360) definition of institutions as "humanly devised constraints that structure human interaction", or simply as "the rules of the game", such rules are likely to encourage creative behaviour of individuals and organisations within an economy, thus promoting innovative activities. For instance, using patent grant data, Tebaldi and Elmslie (2013) found that institutional quality is positively related to patent count across countries. In another study with a large sample of advanced and emerging economies, Silve and Plekhanov (2015) found that institutions are important determinants of innovation and, furthermore, that industries involving higher levels of innovation develop faster in countries with better economic institutions. Using GII data, Sohn et al. (2016) found a positive and indirect relationship between institutions and both knowledge and technological outputs and creative outputs. Therefore, we propose the following hypothesis.

H2a: Institutions have a positive relationship with Innovation Outputs.
H2b: Institutions have a positive relationship with Knowledge and Technology Outputs.

H2c: Institutions have a positive relationship with Creative Outputs.

Human Capital and Research refers to the level of education and research of countries. Van Hiel et al. (2018), using a large sample of countries with great variation in terms of Human Development Index (HDI), found that increasing levels of education, in high HDI countries, translates into better scores on national indices of innovation through the increase of liberalization values in such societies. Also, Suseno et al. (2018) found that human capital and social capital have a significant effect on national innovation performance. Regarding the role of research on innovation, Bilbao-Osorio and Rodriguez-Pose (2004) conclude that overall R&D activities are positively related to innovation in the European Union (EU), while publicly funded R&D is more related to innovation than private R&D in peripheral regions of the EU. Sohn et al. (2016) found positive direct and indirect relationships between Human Capital and Research and both output pillars. Such empirical evidence leads us to propose the following hypothesis.

H3a: Human Capital and Research have a positive relationship with Innovation Outputs.
H3b: Human Capital and Research have a positive relationship with Knowledge and Technology Outputs.
H3c: Human Capital and Research have a positive relationship with Creative Outputs.

According to Cornell University et al. (2018: 59), "good and ecologically friendly communication, transport, and energy infrastructures facilitate the production and exchange of ideas, services and goods". For example, Cuevas-Vargas et al. (2016) found that the use of ICTs is a critical facilitator of innovation for micro, small, and medium-sized enterprises in Mexico. Also, Martins and Veiga (2018) conclude that innovations in Portugal's electronic government can lead to a more business-friendly environment, by reducing the administrative and regulatory burden. According to research by Sohn's et al. (2016), Infrastructure has an indirect, positive, relationship with the two output pillars. Therefore, we propose the following hypothesis.

H4a: Infrastructure has a positive relationship with Innovation Outputs.
H4b: Infrastructure has a positive relationship with Knowledge and Technology Outputs.
H4c: Infrastructure has a positive relationship with Creative Outputs.

Economic and finance literature reveals a relationship between financial market development and economic growth (Beck & Levine, 2002; King & Levine, 1993; La Porta et al., 1998). Fagerberg and Srholec (2008) stressed the importance of a country's financial system in mobilizing the necessary resources for innovation. Empirically, based on a three decade panel of U.S. issued patents, Kortum and Lerner (2000) found that venture capital has a positive and significant impact on technological innovation. Also, Sohn et al. (2016) discovered a positive direct relationship between this pillar and both output pillars. Thus, we propose the following hypothesis.

H5a: Market Sophistication has a positive relationship with Innovation Outputs.
H5b: Market Sophistication has a positive relationship with Knowledge and Technology Outputs.
H5c: Market Sophistication has a positive relationship with Creative Outputs.

The Business Sophistication pillar refers to knowledge workers (i.e. human capital employed by businesses), innovation linkages (i.e. linkages and partnerships between private, public and academic actors), and knowledge absorption (i.e. all high-tech and ICT imports, intellectual property payments, FDI inflows, and researchers in business enterprises) (Cornell University et al., 2018). For instance, Love and Mansury (2007), studying US business services, found that a highly qualified working force increases the probability of innovation. The authors also found that external linkages improve innovation performance. A study on Italian firms conducted by Maietta (2015) suggests that R&D collaboration between businesses and universities has an impact on process innovation and a positive effect on product innovation for firms geographically closer to such entities. Also, Díez-Vial and Montoro-Sánchez (2016) found a positive relationship between the knowledge obtained by technology firms from universities and their levels of innovation. Regarding knowledge absorption, Liu and Zou (2008) found that R&D greenfield FDI significantly affects the innovation performance of domestic firms, finding evidence of both intra and inter-industry spillovers. Also, Bertschek (1995) and Blind and Jungmittag (2004) found that both imports and inward FDI have positive and significant effects on product and process innovations. Again, Sohn et al. (2016) discovered a positive direct relationship between the Business Sophistication pillar and both output pillars. In this sense, we propose the following hypothesis.

H6a: Business Sophistication has a positive relationship with Innovation Outputs.
H6b: Business Sophistication has a positive relationship with Knowledge and Technology Outputs.
H6c: Business Sophistication has a positive relationship with Creative Outputs.

4. METHODOLOGY

4.1 Data and sample

Using the scores provided by the longitudinal GII framework put forward in section 3, we have developed a panel dataset composed of the 19 Eurozone countries during the period 2013 to 2018. It is worth noting that Latvia and Lithuania only joined the Eurozone in 2014 and 2015, respectively, hence resulting in an unbalanced panel with 111 country-year observations.

4.2 Dependent variables

To analyse the relationship between innovation inputs and outputs, we used three dependent variables in separate models. First, the output sub-index (Iout) is used to assess the effect of inputs on the overall score of innovation outputs. Then, we used the two output pillars (Knowledge and Technology Outputs (O6) and Creative Outputs (O7)) to further look into the effects of innovation inputs in each outcome.

4.3 Independent variables

The explanatory variables used are the scores of the innovation input sub-index (Iin), the five input pillars, Institutions (I1), Human Capital and Research (I2), Infrastructure (I3), Market Sophistication (I4), and Business Sophistication (I5), and the 15 input sub-pillars referred to in Figure 1.

4.4 Model specification

When conducting linear regressions with panel data, several estimators could be used, the most common being the pooled ordinary least squares (pOLS), the fixed effects estimator (FE), and the random effects estimator (RE) (Baltagi, 2015; Wooldridge, 2016). To choose an appropriate model, one must consider the nature and source of the data, as well as the methodology used to obtain it (for a discussion, see Hsiao, 2007). Apart from the theoretical discussion, a set of statistical tests can be used to choose a particular model, namely an F test on the joint significance of differing group means (H0 = pOLS; H1 = FE), a Breusch-Pagan test using a Lagrange Multiplier (H0 = pOLS; H1 = RE), and a Hausman test (H0 = RE; H1 = FE).

In this sense, we developed seven regression models with the FE specification, since the aforementioned statistical tests indicated that a FE approach was appropriate. Therefore, to test hypothesis H1, we developed the following model:

$$Iout_{it} = \beta_1 Iin_{it} + \delta_1 d14_t + \delta_2 d15_t + \delta_3 d16_t + \delta_4 d17_t + \delta_5 d18_t + \alpha_i + \mu_{it} \qquad [1]$$

In Eq. 1, Iout is the dependent variable for each country (i) in each year (t), β_1 is the slope of the variable of interest, δ_k (K=1,2,3,4,5) are the coefficients of year dummies included in the regression, α_i is the individual fixed effect that does not vary over time, and μ_{it} is the idiosyncratic error. We follow the Wooldridge (2016) recommendation to include time dummies if T is small relative to N (in this case, T=6 and N=19), to capture secular changes that are not being modelled. To test hypothesis H2a, H3a, H4a, H5a, and H6a, we developed the following model:

$$Iout_{it} = \beta_1 I1_{it} + \beta_2 I2_{it} + \beta_3 I3_{it} + \beta_4 I4_{it} + \beta_5 I5_{it} + \delta_1 d14_t + \delta_2 d15_t + \delta_3 d16_t + \delta_4 d17_t + \delta_5 d18_t + \alpha_i + \mu_{it} \qquad [2]$$

In Eq. 2, β_k (K=1, 2, 3, 4, 5) are the slopes of the variables of interest, which are the five input pillars. The following model was developed to test hypothesis H2b, H3b, H4b, H5b, and H6b:

$$O6_{it} = \beta_1 I1_{it} + \beta_2 I2_{it} + \beta_3 I3_{it} + \beta_4 I4_{it} + \beta_5 I5_{it} + \delta_1 d14_t + \delta_2 d15_t + \delta_3 d16_t + \delta_4 d17_t + \delta_5 d18_t + \alpha_i + \mu_{it} \qquad [3]$$

In Eq. 3, O6 refers to the Knowledge and Technology Outputs. To test hypothesis H2c, H3c, H4c, H5c, and H6c, we developed the following model:

$$O7_{it} = \beta_1 I1_{it} + \beta_2 I2_{it} + \beta_3 I3_{it} + \beta_4 I4_{it} + \beta_5 I5_{it} + \delta_1 d14_t + \delta_2 d15_t + \delta_3 d16_t + \delta_4 d17_t + \delta_5 d18_t + \alpha_i + \mu_{it} \qquad [4]$$

In Eq. 4, O7 refers to Creative Outputs. Lastly, to allow for a finer analysis, we developed three regression models with inputs decomposed up to the sub-pillar level:

$$\begin{gathered} Iout_{it} = \beta_1 I11_{it} + \beta_2 I12_{it} + \beta_3 I13_{it} + \beta_4 I21_{it} + \beta_5 I22_{it} + \beta_6 I23_{it} + \beta_7 I31_{it} + \beta_8 I32_{it} + \beta_9 I33_{it} + \beta_{10} I41_{it} + \\ \beta_{11} I42_{it} + \beta_{12} I43_{it} + \beta_{13} I51_{it} + \beta_{14} I52_{it} + \beta_{15} I53_{it} + \delta_1 d14_t + \delta_2 d15_t + \delta_3 d16_t + \delta_4 d17_t + \delta_5 d18_t + \alpha_i + \mu_{it} \end{gathered} \qquad [5]$$

$$\begin{gathered} O6_{it} = \beta_1 I11_{it} + \beta_2 I12_{it} + \beta_3 I13_{it} + \beta_4 I21_{it} + \beta_5 I22_{it} + \beta_6 I23_{it} + \beta_7 I31_{it} + \beta_8 I32_{it} + \beta_9 I33_{it} + \beta_{10} I41_{it} + \\ \beta_{11} I42_{it} + \beta_{12} I43_{it} + \beta_{13} I51_{it} + \beta_{14} I52_{it} + \beta_{15} I53_{it} + \delta_1 d14_t + \delta_2 d15_t + \delta_3 d16_t + \delta_4 d17_t + \delta_5 d18_t + \alpha_i + \mu_{it} \end{gathered} \qquad [6]$$

$$\begin{gathered} O7_{it} = \beta_1 I11_{it} + \beta_2 I12_{it} + \beta_3 I13_{it} + \beta_4 I21_{it} + \beta_5 I22_{it} + \beta_6 I23_{it} + \beta_7 I31_{it} + \beta_8 I32_{it} + \beta_9 I33_{it} + \beta_{10} I41_{it} + \\ \beta_{11} I42_{it} + \beta_{12} I43_{it} + \beta_{13} I51_{it} + \beta_{14} I52_{it} + \beta_{15} I53_{it} + \delta_1 d14_t + \delta_2 d15_t + \delta_3 d16_t + \delta_4 d17_t + \delta_5 d18_t + \alpha_i + \mu_{it} \end{gathered} \qquad [7]$$

In Eqs. 5, 6, and 7, the variables of interest are the Political Environment (I11), Regulatory Environment (I12), Business Environment (I13), Education (I21), Tertiary Education (I22), Research and Development (I23), ICTs (I31), General Infrastructure (I32), Environmental Sustainability (I33), Credit (I41), Investment (I42), Trade, Competition, and Market Scale (I43), Knowledge Workers (I51), Innovation Linkages (I52), and Knowledge Absorption (I53).

5. RESULTS AND DISCUSSION

Table 1 shows the main descriptive statistics, the correlation matrix, and variance inflation factors (VIF). An analysis of the correlation matrix reveals the existence of significant correlations between the variables. Although a high correlation was expected between the input and output sub-indexes and their respective pillars, the existing correlations between the five input pillars could result in multicollinearity issues when regressed together. However, the highest VIF value (1.997 for variable I1) is below the common rule of thumb of 10 (Wooldridge, 2016), which suggests that multicollinearity should not be a problem.

Table 1: Descriptive statistics, correlation matrix and variance inflation factors (VIF).

	N	Mean	S.D.	Iout	O6	O7	Iin	I1	I2	I3	I4	I5
Iout	111	36.14	4.50	-								
O6	111	24.24	4.40	0.857	-							
O7	111	48.05	5.70	0.917	0.581	-						
Iin	111	42.51	4.19	0.812	0.851	0.625	-					
I1	111	60.10	5.29	0.585	0.641	0.428	0.799	**1.997**				
I2	111	35.19	7.75	0.677	0.724	0.509	0.855	0.598	**1.909**			
I3	111	48.97	6.00	0.439	0.470	0.330	0.574	0.312	0.415	**1.319**		
I4	111	39.47	5.85	0.383	0.466	0.245	0.519	0.332	0.314	-0.072	**1.236**	
I5	111	28.84	4.74	0.799	0.689	0.730	0.759	0.628	0.557	0.326	0.264	**1.830**

Note: Correlation values above 0.1865 are significant at the 5% level (two-tailed). VIF values are presented in the diagonal, in bold.
Source: Own elaboration.

Table 2 displays the results of the regressions used to test our hypothesis. Regarding the inclusion of time dummies, a Wald joint test rejects the null hypothesis of no time effects.

Table 2: Results of Fixed Effects regressions

Dependent Variable	**Iout**	**Iout**	**O6**	**O7**
Model	FE (1)	FE (2)	FE (3)	FE (4)
Iin	0.254 (0.226)	-	-	-
I1	-	-0.019 (0.111)	0.055 (0.142)	-0.093 (0.115)
I2	-	-0.055 (0.049)	0.007 (0.048)	-0.117 (0.073)
I3	-	-0.002 (0.092)	0.091 (0.114)	-0.095 (0.089)
I4	-	-0.001 (0.110)	-0.025 (0.118)	0.023 (0.126)
I5	-	0.299* (0.121)	0.298† (0.153)	0.300* (0.132)
N	111	111	111	111
Within R^2	0.3893	0.5129	0.4183	0.6183
BIC	447.751	441.491	466.980	516.625
Time dummies	Yes	Yes	Yes	Yes
Wald F (5, 18)	14.896***	19.243***	8.153***	18.993***

Note: † $p \leq 0.1$; * $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$. Below the coefficients are heteroskedasticity and autocorrelation (HAC) robust standard errors, in parenthesis.

Source: Own elaboration.

With the first model we intended to test if, in Eurozone countries, innovation inputs (Iin) are, in fact, transformed into innovation outputs (Iout) (Column 1, Table 2). Results reveal a positive relationship between Innovation Inputs and Outputs, without attaining statistical significance. Although correctly signed, it does not attest to the presence of statistically significant relationship, hence not supporting Hypothesis H1.

When decomposing innovation inputs into pillars (Column 2, Table 2), only the Business Sophistication pillar showed a statistically significant relationship with the Innovation Outputs sub-index ($p = 0.0346$), with a positive sign, thus supporting Hypothesis H6a. The remaining coefficients, although not statistically significant, revealed a negative sign, failing to support Hypotheses H2a, H3a, H4a, and H5a.

The positive effect of the Business Sophistication pillar suggests that the employment of knowledge workers, the quality of linkages between public organizations, universities, and private firms, and the economy's knowledge absorption capacity are strong inducers of innovation in a country. This result adds to previous empirical research on countries in the Eurozone (Bertschek, 1995; Blind & Jungmittag, 2004; Díez-Vial & Montoro-Sánchez, 2016; Maietta, 2015).

Columns 3 and 4 (Table 2) show the results of regressing the five input pillars on the two output pillars. Analysing the effects of input pillars on Knowledge and Technology Outputs (O6) (Column 3, Table 2), we found that only Business Sophistication has a significant effect ($p = 0.0678$) with a positive sign, thus supporting Hypothesis H6b. As such, results do not lend support for Hypothesis H2b, H3b, H4b, and H5b. However, a negative, albeit not statistically significant, effect of Market Sophistication (I4) on Knowledge and Technology Outputs (O6) was also found. In Column 4 (Table 2), once more Business Sophistication was the only input pillar that revealed a positive, statistically significant relationship ($p = 0.0361$) with Creative Outputs (O7), supporting Hypothesis H6c. The remaining coefficients did not attain statistical significance, although three presented a negative sign (Institutions, Human Capital and Research, and Infrastructure), thus not supporting Hypothesis H2c, H3c, H4c, and H5c.The negative signs are likely due to time lags in the relationships. As a robustness test, we have introduced a one-year time lag in all dependent variables, except in Business Sophistication. Results remained essentially the same, although the Human Capital and Research, and Market Sophistication pillars changed to positive signs.

Further analysis of the Eurozone, by decomposing the independent variables into their 15 input sub-pillars, is shown in table 3. This detailed analysis reveals which sub-pillars are responsible for the results presented above.

Table 3: Results of Fixed Effects regressions using all input sub-pillars (Eurozone sub-sample)

Dependent Variable	Iout	O6	O7

Model	FE (5)	FE (6)	FE (7)
I11	0.074	0.035	0.113
	(0.120)	(0.116)	(0.183)
I12	-0.064	0.023	-0.151
	(0.054)	(0.039)	(0.095)
I13	0.034	0.032	0.036
	(0.050)	(0.067)	(0.066)
I21	0.010	0.025	-0.005
	(0.016)	(0.021)	(0.032)
I22	-0.093	-0.093	-0.093
	(0.066)	(0.090)	(0.056)
I23	-0.104**	-0.042	-0.165**
	(0.031)	(0.033)	(0.043)
I31	-0.039	-0.014	-0.065
	(0.036)	(0.043)	(0.043)
I32	-0.019	-0.002	-0.035
	(0.094)	(0.097)	(0.101)
I33	0.114**	0.163**	0.065
	(0.038)	(0.051)	(0.088)
I41	-0.025	-0.047	-0.003
	(0.052)	(0.053)	(0.072)
I42	0.000	0.018	-0.018
	(0.043)	(0.055)	(0.057)
I43	0.187*	0.168	0.205†
	(0.076)	(0.108)	(0.107)
I51	0.057	0.037	0.078
	(0.042)	(0.052)	(0.077)
I52	-0.016	-0.019	-0.013
	(0.062)	(0.059)	(0.107)
I53	0.211***	0.228**	0.195***
	(0.053)	(0.069)	(0.041)
N	111	111	111
Within R^2	0.6476	0.5795	0.6785
BIC	452.664	478.036	544.667
Time dummies	Yes	Yes	Yes
Wald F (5, 18)	10.575***	6.186**	9.807***

Note: † $p \leq 0.1$; * $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$. Below the coefficients are heteroskedasticity and autocorrelation (HAC) robust standard errors, in parenthesis.
Source: Own elaboration.

A negative and statistically significant relationship was found between Research and Development (I23) and Creative Outputs (p = 0.0013) (Column 15, Table 5), while the relationship with Knowledge and Technology Outputs (O6) does not show the same statistical significance, albeit with a negative sign still (Column 14, Table 5). Ecological Sustainability (I33) shows a positive, statistically significant, relationship with Knowledge and Technology Outputs (p = 0.0048). The trade, Competition, and Market Scale (I43) also presents a positive and statistically significant relationship with Creative Outputs (p = 0.0718), below the 10% level. Perhaps the most revealing result is the positive relationship, with a strong statistical significance, between Knowledge Absorption (I53) and both Knowledge and Technology Outputs (p = 0.0041) and Creative Outputs (p = 0.0002).

Regarding the relationship between Business Sophistication and both output pillars, it can be seen that its effects derive from the Knowledge Absorption sub-pillar, which includes intellectual property payments, high-tech imports, imports of ICT services, FDI inflows, and researchers in business enterprises. A panel study of German manufacturing firms (Bertschek, 1995) concluded that both imports and inward FDI had positive and significant effects on product and process innovations. Also, Blind and Jungmittag (2004) conducted a similar - albeit cross-sectional - study on German service firms, which produced very similar results. In another study, Liu and Zou (2008) concluded that imports and the various forms of inward FDI in China improved the levels of innovation of domestic firms'.

6. Spanish Innovation Performance

In this section, we describe Spain's innovation performance over time and relative to the Eurozone. Table 4 shows Spain's overall ranking, revealing a drop from 2013 to 2018. This shift in positions can be explained partially by the Spanish performance and partially by other countries' performance. Table 4 also shows Spain's scores down to the pillar level, revealing some trends over time. Almost all pillars present a deterioration from 2013 to 2018, with the exception of Institutions (+3.6%) and Infrastructure (+21.8%). The largest negative variations from 2013 to 2018 are Business Sophistication (-21.7%) and Human Capital and Research (-14.6%).

Table 4: Spain GII rankings and scores

Variable	2013	2014	2015	2016	2017	2018	Δ 13/18
Spain GII ranking	22	22	22	24	25	24	-2
Input sub-index	43.24	43.25	44.14	43.60	43.98	42.27	-2.2%
Output sub-index	36.89	36.62	36.80	34.69	33.75	34.19	-7.3%
GII score	40.06	39.94	40.47	39.15	38.86	38.23	-4.6%
Innovation Efficiency Index	0.85	0.85	0.83	0.80	0.77	0.81	-5.2%
Input pillars:							
Institutions	55.29	53.13	55.96	56.57	57.64	57.27	3.6%
Human Capital and Research	36.70	36.51	35.60	35.44	34.79	31.33	-14.6%
Infrastructure	46.56	49.07	53.42	55.73	57.95	56.69	21.8%
Market Sophistication	49.73	49.45	48.39	46.06	44.67	44.21	-11.1%
Business Sophistication	27.92	28.06	27.33	24.21	24.86	21.87	-21.7%
Output pillars:							
Knowledge and Technology Outputs	26.09	26.39	25.78	25.15	25.01	23.17	-11.2%
Creative Outputs	47.69	46.86	47.83	44.24	42.48	45.21	-5.2%

Source: Own elaboration.

Table 5 shows a comparison of the Spanish scores against Eurozone average and Eurozone Top 3 performers' averages, down to the pillar level, revealing that Spain has room for improving its innovation convergence with its monetary partners. In a first analysis, looking at the main indices, it can be seen that Spain's innovation inputs are consecutively above Eurozone average, while innovation outputs are mainly below average. This consequently puts Spain below the Eurozone in terms of innovation efficiency. When compared with the top 3 performers, Spain is lagging behind in all main indicators. On the pillar level, when compared to the Eurozone, Spain exhibits positive gaps in the Infrastructure (+7.7% in 2018), Market Sophistication (+17.9% in 2018), and Knowledge and Technology Outputs (+1.7% in 2018) pillars. Also worthy of highlight, Spain's largest negative gap concerns Business Sophistication pillar, which reached its peak in 2018 (-18.9%), revealing an area worthy of improvement. Besides Business Sophistication, other negative gaps towards the Eurozone exist, under Institutions (-4.1% in 2018), Human Capital and Research (-0.3% in 2018), and Creative Outputs (-4.4% in 2018).

Table 5: Yearly scores of Spain *versus* Eurozone and Eurozone Top 3 means

Variable		**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Input sub-index	Spain	43.24	43.25	44.14	43.60	43.98	42.27
	Eurozone	42.28	42.24	42.72	42.70	43.45	41.66
	Eurozone Top 3	48.46	49.04	49.01	48.99	49.07	47.10
	Δ Spain vs Eurozone	2.3%	2.4%	3.3%	2.1%	1.2%	1.5%
	Δ Spain vs Top 3	-10.8%	-11.8%	-9.9%	-11.0%	-10.4%	-10.2%
Output sub-index	Spain	36.89	36.62	36.80	34.69	33.75	34.19
	Eurozone	37.83	36.24	36.87	36.05	35.02	35.04
	Eurozone Top 3	43.39	42.41	43.95	43.06	42.12	42.82
	Δ Spain vs Eurozone	-2.5%	1.1%	-0.2%	-3.8%	-3.6%	-2.4%
	Δ Spain vs Top 3	-15.0%	-13.6%	-16.3%	-19.4%	-19.9%	-20.2%
GII	Spain	40.06	39.94	40.47	39.15	38.86	38.23
	Eurozone	40.06	39.24	39.80	39.37	39.24	38.35
	Eurozone Top 3	45.25	45.24	46.14	45.77	45.41	44.52
	Δ Spain vs Eurozone	0.0%	1.8%	1.7%	-0.6%	-1.0%	-0.3%
	Δ Spain vs Top 3	-11.5%	-11.7%	-12.3%	-14.5%	-14.4%	-14.1%
Innovation Efficiency Index	Spain	0.853	0.847	0.834	0.796	0.767	0.809
	Eurozone	0.897	0.859	0.862	0.844	0.805	0.840
	Eurozone Top 3	0.953	0.918	0.930	0.950	0.917	0.964
	Δ Spain vs Eurozone	-4.9%	-1.4%	-3.3%	-5.7%	-4.7%	-3.7%
	Δ Spain vs Top 3	-10.5%	-7.8%	-10.4%	-16.3%	-16.3%	-16.1%
Input pillars:							
Institutions	Spain	55.29	53.13	55.96	56.57	57.64	57.27
	Eurozone	59.82	59.44	60.14	60.71	60.72	59.74
	Eurozone Top 3	70.00	69.58	68.73	69.00	67.70	66.94
	Δ Spain vs Eurozone	-7.6%	-10.6%	-6.9%	-6.8%	-5.1%	-4.1%
	Δ Spain vs Top 3	-21.0%	-23.6%	-18.6%	-18.0%	-14.9%	-14.5%
Human Capital and Research	Spain	36.70	36.51	35.60	35.44	34.79	31.33
	Eurozone	36.32	35.16	36.36	35.99	35.98	31.44
	Eurozone Top 3	48.73	48.06	48.29	48.95	48.03	41.74
	Δ Spain vs Eurozone	1.0%	3.9%	-2.1%	-1.5%	-3.3%	-0.3%
	Δ Spain vs Top 3	-24.7%	-24.0%	-26.3%	-27.6%	-27.6%	-24.9%
Infrastructure	Spain	46.56	49.07	53.42	55.73	57.95	56.69
	Eurozone	43.71	44.95	48.15	50.42	53.19	52.64
	Eurozone Top 3	50.90	52.64	54.54	56.59	57.63	58.82
	Δ Spain vs Eurozone	6.5%	9.2%	10.9%	10.5%	9.0%	7.7%
	Δ Spain vs Top 3	-8.5%	-6.8%	-2.1%	-1.5%	0.6%	-3.6%
Market Sophistication	Spain	49.73	49.45	48.39	46.06	44.67	44.21
	Eurozone	41.74	42.24	40.20	37.79	37.76	37.51
	Eurozone Top 3	51.20	51.02	48.67	45.88	44.70	43.97
	Δ Spain vs Eurozone	19.1%	17.1%	20.4%	21.9%	18.3%	17.9%
	Δ Spain vs Top 3	-2.9%	-3.1%	-0.6%	0.4%	-0.1%	0.5%
Business Sophistication	Spain	27.92	28.06	27.33	24.21	24.86	21.87
	Eurozone	29.81	29.43	28.77	28.58	29.58	26.97
	Eurozone Top 3	37.97	36.16	36.34	35.36	36.50	33.15

	Δ Spain vs Eurozone	-6.3%	-4.6%	-5.0%	-15.3%	-16.0%	-18.9%
	Δ Spain vs Top 3	-26.5%	-22.4%	-24.8%	-31.5%	-31.9%	-34.0%
Output pillars:							
Knowledge and Technology Outputs	Spain	26.09	26.39	25.78	25.15	25.01	23.17
	Eurozone	25.45	24.03	23.84	24.60	24.85	22.79
	Eurozone Top 3	31.74	30.74	30.95	32.17	32.03	29.35
	Δ Spain vs Eurozone	2.5%	9.8%	8.1%	2.2%	0.7%	1.7%
	Δ Spain vs Top 3	-17.8%	-14.1%	-16.7%	-21.8%	-21.9%	-21.1%
Creative Outputs	Spain	47.69	46.86	47.83	44.24	42.48	45.21
	Eurozone	50.22	48.45	49.90	47.50	45.19	47.28
	Eurozone Top 3	57.31	55.56	57.80	56.54	54.41	57.33
	Δ Spain vs Eurozone	-5.0%	-3.3%	-4.1%	-6.9%	-6.0%	-4.4%
	Δ Spain vs Top 3	-16.8%	-15.7%	-17.2%	-21.8%	-21.9%	-21.1%

Source: Own elaboration.

Comparing Spain to the three best performers in the Eurozone, Table 5 reveals that, in 2018, the largest gap was in the Business Sophistication pillar (-34.0%), followed by Human Capital and Research (-24.9%) and both output pillars (-21.1%). Regarding Market Sophistication, Spain is already among the top 3 performers, hence a positive variation (+0.5% in 2018).

6.1. Implications for Spain

Following the results obtained in section 5, we now derive some implications for Spain, regarding improvements in its comparative levels of innovation. We start with a simple exercise, with which we intend to demonstrate the importance of certain policies for the convergence of Spain with the Eurozone. First, we have selected the Knowledge Absorption sub-pillar due to its significant effects on both innovation outputs and because it belongs to the pillar in which the negative gap between Spain and the Eurozone was larger. We computed the difference between the Spanish (28.448) and the Eurozone's average scores (32.135) (averages for the period 2013-2018). The value was then multiplied by the estimated coefficient of Knowledge Absorption (I53) in each of the regressions presented in Table 3. The same reasoning was made for the top Eurozone performer, which, for this sub-pillar, is the Netherlands (48.441).

Table 6 shows potential benefits for innovation outputs if policies are developed to improve Spanish business sophistication, namely those related to the Knowledge Absorption sub-pillar. As mentioned above, Business Sophistication is the pillar where Spain has the largest negative gap vis-à-vis the Eurozone, with an average difference of -11.0%, and -28.5% in relation to the Eurozone best performers. Recalling Table 3, policies towards the attraction of FDI, or incentives to high-tech imports, are likely to enhance Spanish innovation output performance, and, consequently, its innovation efficiency. However, caution must be taken when interpreting these results, since, as suggested by Liu and Zou (2008), different kinds of FDI might have differentiated effects on innovation performance. Another area worthy of improvement is Infrastructure, namely the sub-pillar of Ecological Sustainability, which revealed a positive effect on Knowledge and Technology

Outputs. Although Spain stands above the Eurozone average in the Infrastructure pillar, an improvement of the country environmental performance could draw it closer to the top performers in the Eurozone, for instance, encouraging firms to comply with ISO 14001 certification or increasing energy use efficiency. Concerning the negative relationships found, further research is needed to understand their causes before implications can be drawn.

Table 6: Estimated impact of Iberia's convergence on the Knowledge Absorption sub-pillar with the Eurozone average and top performer

Variable	Estimated coefficient for Knowledge Absorption	Impact of convergence with the Eurozone average	Impact of convergence with the top Eurozone performer (The Netherlands)
Iout	0.211	0.778	4.218
O6	0.228	0.841	4.558
O7	0.195	0.719	3.899

Source: Own elaboration.

7. Conclusions

With this paper we sought to understand which innovation inputs contributed the most to innovation outputs in the Eurozone in an effort to derive policy implications for Spain. To that end, we have adopted the framework provided by the Global Innovation Index (Cornell University et al., 2018), due to its clear distinction between innovation inputs and outputs and, acknowledging methodological limitations induced by its own cross-sectional nature, we have developed our own longitudinal GII.

Overall, results suggest that the Business Sophistication pillar is the major driver of innovation outputs in the Eurozone, and it is precisely in this regard that Spain is lagging behind the most. A further analysis revealed that those effects came essentially from areas such as the imports of high-tech goods, ICT services, and knowledge, as well as the presence of researchers in businesses and inward FDI. This suggests that the overall Knowledge Absorption of countries in the Eurozone is key to determining their innovative readiness. Therefore, we argue that policies directed at improving domestic firms' knowledge absorption capacity, such as incentives to high-tech imports or encouraging inward FDI, are likely to enhance Spanish innovative outputs, especially benefiting from the convergence with Eurozone's top innovators.

Some surprising results arose in the analysis, namely the negative relationship between the Research and Development (I23) sub-pillar and Creative Outputs (O7). Such result should be addressed with caution, since investments in these areas tend to take some years to pay off. Also, several pillars revealed negative relationships with innovation outputs, although without statistical significance. Again, such outputs are likely to take much time to be result in outputs. Furthermore, regarding institutions, Goedhuys et al. (2016) stresses that corruption can take the role of "grease in the wheels" when institutional obstacles are encountered, being otherwise an impediment to innovation of firms in sound business environments.

7.1 Limitations and future research

As with every research, our study has its limitations which ought to be acknowledged. The use of an index could be, in itself, a limitation. Nonetheless, we consider it a solid indicator of national innovativeness, since it blends hard data with experts' opinions on a number of issues. Furthermore, the Global Innovation Index is developed by some of the most important business and economics schools in cooperation with major international organisations. The limited time period available impedes a longer analysis of the influence of certain variables, whose effects we believe could be felt further down the road. This limitation could be of extreme importance regarding the negative effects found throughout the paper, since investments in certain areas, such as education, R&D, or public infrastructures, might require several years to attain the desired outcome. As such, further research is necessary to explore the causes of negative relationships between innovation inputs and outputs found in this paper. Another possibly relevant constraint is the absence of control variables, commonly found in this type of empirical analysis (e.g. Martins & Veiga, 2018). However, the indicators used in the construction of this index already contemplate the vast majority of controls used in the literature. Last, research is needed regarding the most significant results of this study, the impact of Knowledge Absorption on both innovation outputs. Notwithstanding the other indicators relating to imports of goods, services, and knowledge, and the presence of researchers in businesses, we consider that inward FDI plays a major role in the innovative capacity of a country, mainly due to its dual effect on domestic firms: first, by increasing the competition in the local market, domestic firms tend to innovate to maintain their market position (Bertschek, 1995; Blind & Jungmittag, 2004); and second, different types of FDI could have differentiated effects on the capacity of domestic undertakings to innovate (Liu & Zou, 2008). Owing to the latter effect, Liu and Zou (2008) found that greenfield R&D FDI presented both intra- and inter-industry spillovers, while mergers and acquisitions produced only inter-industry spillovers. To derive finer implications for Spain, one should rely on firm level FDI data, thus being able to control other firm's factors that cannot be measured at the country level.

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