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Portuguese Regional Innovation Systems Efficiency in the European Union Context

Current evidence on European regional innovation systems efficiency shows some conflicting results. Whereas some studies find support to a core-periphery distribution of efficiency, others find that lagging regions can be as well or even more efficient than rich regions in using their resources. This paper contribute to this debatable topic by providing additional evidence on the main determinants of region´s innovation efficiency and on efficiency differentials across EU regional innovation systems. Using data from 206 European regions and applying a stochastic production frontier methodology, our results corroborate the importance of interactions among regional agents on region´s efficiency score. More importantly, the distribution of efficiency scores across regional innovation systems does not entirely confirm the core-periphery divide among European regions. Instead, the mode of doing innovation appears to be a crucial explanatory factor of innovation efficiency at regional level. In the case of Portuguese regional innovation systems, they perform slightly below the average of their EU counterparts, except Lisbon´s, and appear to be constrained by their mode of doing innovation.

Keywords: Regional innovation systems; production frontier; technical efficiency; European Union.

JEL codes: O11, O18, O32, O47

Introduction

The concept of innovation system (IS), originally conceived by Freeman (1984) and later developed by Lundvall (1992) and Nelson and Rosenberg (1993), refers to the set of agents that are involved and interact in the process of production and diffusion of innovation, and it helps to explain the economic performance of nations, regions, sectors and technologies. A central idea of the approach presented by Freeman (1984) is that the rate of technological change and innovation is shaped by a set of multiple factors and agents, such as firms, universities, government, and investors, as well as by the quality of the interactions among them. The topic has received increasing attention from both scholars and public decision makers and, nowadays, the development of national and regional innovation systems have a prominent role in the territorial dynamics of competitiveness and innovation (e.g. Asheim and Coenen, 2006; Asheim and Gertler, 2005; Asheim et al., 2011; Camagni and Capello, 2013; Capello and Lenzi, 2013a; and see Doloreux and Gomez, 2017 for a literature review).

In the wake of these contributions, a growing number of studies has investigated the way different regions innovate and their relative efficiency in doing so (e.g. Broekel et al., 2018; Capello and Lenzi, 2013a, 2013b; Carayannis et al. 2016; Fritsch and Slavtchev, 2011; Kaihua and Mingting, 2014; Kalapouti et al., 2017; Nasierowski, 2010; Nasierowski and

Arcelus, 2012; Zabala-Iturriagagoitia et al., 2007). Two key results have emerged from these contributions: regions are very heterogenous regarding their *efficiency* in using resources as well as in their *mode* in doing innovation. Furthermore, some of these studies have found evidence indicating that neither innovation (Capello and Lenzi, 2013b) nor efficiency in doing innovation is exclusive to the richest regions (e.g. Carayannis et al. 2016; Matei and Spircu, 2012; Zaballa-Iturriagagoitia et al., 2007). This evidence is at odds with the European Commission view (EC, 2014), which identifies as best practices those of the regions with more investment in innovation activities neglecting regions with less investment but with growth potential (Leydesdorff and Fritsch, 2006; Edquist and Zabala-Iturriagagoitia, 2015). Therefore, additional research is needed to provide more detailed insights in understanding the nature and dynamics of regional innovation efficiency.

From a policy point of view, additional knowledge on the nature and dynamics of regional innovation efficiency is relevant because it could change the locus of innovation policy from quantity to quality, in the sense that policies should be designed to the region´s specific needs and not necessarily rely only on technological inputs investments (e.g. Asheim et al., 2011; Camagni and Capello, 2013; Capello and Lenzi, 2013a; 2013b; Tödtling and Trippl, 2005). Yet, empirical evidence on the relationship between endowments and innovation and/or efficiency in using resources is not consensual (e.g. Fodi and Usai, 2013;

Fritsch and Slavtchev, 2011; Hajek et al., 2014; Kalapouti et al., 2017), which call for further studies that help to clarify that relationship and to provide evidence on the main determinants of region´s innovation efficiency.

Therefore, the originality and contribution of this paper is twofold. Firstly, we investigate the role of economics agents´ interactions as a main determinant of region´s innovation efficiency by applying a stochastic frontier approach (SFA). Moreover, based on those estimates we are able to obtain technical efficiency scores and to rank EU regional innovation systems. Secondly, we examine the geographical distribution of the regional efficiency scores and the extent to which there are differences in efficiency across different types of regional innovation systems. In order to do so, we apply two alternative taxonomies of territorial innovation; a recent taxonomy of territorial innovation proposed by Capello and Lenzi (2013a) that focuses mainly on modes of innovation in an attempt to overcome the more traditional taxonomies approach and the taxonomy of the Regional Innovation Scoreboard (EC, 2014) which focus on the quantity of resources available to the innovation process. This analysis provides additional empirical evidence on the relationship between efficiency at regional level and regional innovation systems types. By doing so, we provide valuable insight to assess the comparative relevance of resources and mode in doing innovation in improving regional innovation efficiency in the EU context.

Whilst we perform the analysis across 206 NUTS II European regions we also examine Portuguese regions vis-à-vis European counterparts. The economic characteristics of Portugal are shared with other European regions located in the South and East Europe, making it an interesting case to draw evidence from (e.g. Almeida et al., 2011; Fonseca et al., 2018) and to provide valuable insights in the field of innovation system assessment in a peripheral region. Regarding R&D investment, Portugal is a country with similar R&D investment (as a percentage of GDP in 2014) to Spain, Italy and Luxemburg (1–1.5%), but it has made significant improvements in education showing an increase from 12% in 2007, to values similar to Finland (22.4%) and higher than Germany (16.9%). Since joining the European Union (EU), Portugal has received significant financial support towards innovation and R&D (Santos and Simões, 2014) allowing the country to improve significantly its position in the European Commission Regional Innovation Scoreboard rank as it went from a low innovator to a moderate innovate over the last decade. But some studies still find that Portuguese regions are characterized by low productivity of knowledge and they still are undergoing a process of very gradual convergence with respect to high-productivity regions (e.g. Fodi and Usai, 2013). Furthermore, whereas Portuguese regions are traditionally grouped in the moderate to low innovative group of regions similar to other Southern European regions they have been classified quite differently, such as Noninteractive Regions by Moreno and Miguélez (2012) or as Smart and Creative with high potential by Cappelo and Lenzi (2013a). This divergence among alternative taxonomies and its relationship with resources and mode of doing innovation would contribute to a better understanding of best practices in the field of regional innovation.

The paper is divided into the following sections. Section 2 provides a literature review on RIS efficiency evaluation. Section 3 describes the methodology and data. Section 4 presents the empirical results. Finally, section 5 presents the main conclusions

Regional innovation systems and their evaluation

The literature on innovation systems (Fagerberg et al., 2004; Freeman, 1984; Hadjimanolis, 1999; Lundvall, 1992; Nelson and Rosenberg , 1993) states that the capacity and process of innovation is influenced not only by private firms but also by non-entrepreneurial organizations such as universities, research centres, government and institutions (laws, rules, norms and routines) that create incentives or obstacles to the innovation process. In addition, an important feature of the system are the relationships between firms and existing knowledge infrastructure in the system such as universities and research centres (Asheim and Coenen, 2006; Asheim and Gertler, 2005; Camagni and Capello, 2013; Cooke, 1992, 2008;

Doloreux, 2004; Fritsch and Slavtchev, 2011; Lundquist and Trippl, 2013; Tödtling and Trippl, 2005).

Innovation systems can be studied at different levels (e.g. global, national, regional and sectoral); yet, some questions can be raised about the limits and permeability between different systems including the geographical dimension (Asheim et al., 2011) and the activities or functions of the system (Edquist, 2005). These issues can generate some ambiguity regarding the innovation system delineation, thereby making it difficult to implement its evaluation (Vaz et al., 2014). Nonetheless, the importance of the innovation systems approach is nowadays widely recognized in the literature where the regional level has become one of central relevance for the design of regional development policies (Almeida et al., 2011; Asheim and Coenen, 2006; Camagni and Capello, 2013; Capello and Lenzi, 2013a, 2013b; Doloreux, 2004; Edquist, 1997; Fritsch and Slavtchev, 2011; Lundquist and Trippl, 2013; Tödtling and Trippl, 2005). As a result, a growing number of studies has assessed the performance of European regional innovation systems (e.g. Capello and Lenzi, 2013, 2014; Carayannis et al. 2016; Fodi and Usai, 2013; Fritsch and Slavtchev, 2011; Hajek et al., 2014; Kalapouti et al. 2017; Matei and Spircu, 2012; Zabala-Iturriaggoitia et al., 2007).

However, empirical evidence reveals some conflicting results. On one hand, some studies find support to an overall core-periphery view of European regions, in which the richest regions in central Europe are also the most efficient in producing innovation (Fodi and Usai, 2013; Fritsch and Slavtchev, 2011; Hajek et al., 2014; Kalapouti et al., 2017; Moreno and Miguélez, 2012). On the other hand, some evidence suggests that resource-rich regions are not necessarily those that achieve higher performance levels (Carayannis et al. 2016; Matei and Spircu, 2012; Matei and Spircu, 2012; Zabala-Iturriaggoitia et al., 2007). Table 1 presents a summary of selected evidence on regional innovation efficiency by emphasising differences on empirical methodology, characteristics of best performers and region types.

INSERT TABLE 1 HERE

Overall, evidence based on measures like patents or methodologies mainly oriented to the inputs in the system in the sense of ´the more the better´ (regression and indices) tends to favour regions with more resources, whereas methodologies oriented towards efficiency show mixed findings as regions with consolidated innovation systems do not show efficiency levels commensurate with their expected competitiveness (Carayannis et al., 2016).

One possible explanation is that regions with higher technological levels have a greater need for coordination of the regional innovation system and, for this reason, lower levels of efficiency compared to other regions with lower innovation investments

(Georghiou, 2001; Zabala-Iturriaggoitia et al., 2007). Moreover, modes of doing innovation favouring radical innovations, which are more risky and require higher levels of resources and coordination, are more likely in regions with higher technological levels. As such, a high need of coordination and development associated to large risk of the adopted mode of doing innovation could comparatively render lower levels of efficiency.

Another avenue to understand innovation differences across regions are regional innovation systems taxonomies, such as those proposed by Asheim and Gertler (2005), Camagni and Capello (2013), Capello and Lenzi (2013a), Moreno and Miguélez (2012) or by Tödtling and Trippl (2005). Whereas some typologies (Moreno and Miguélez, 2012) identify patterns of innovation at the regional level using mainly innovation and knowledge indicators (such as R&D and patents), others seek a classification based on types of knowledge and learning (Asheim and Gertler, 2005; Tödtling and Trippl, 2005) or innovation modes and contexts in which innovation takes place (Capello and Lenzi, 2013a). The former tends to assess regional innovation systems with more endowments in R&D and patents more favourably than innovation systems located in poorer regions and/or with less endowment in innovation inputs. The latter, namely by Capello and Lenzi (2013a), provide a richer explanation for territorial patterns of innovation. This framework has been now conceptually accepted and empirically proved (Capello & Lenzi, 2013b, 2015) and presents the advantage of considering all types of innovations, from radical to imitative ones and different modes of doing and attaining innovation (Capello and Lenzi, 2017).

Another explanation for conflicting evidence relates the methodology and the measure employed to assess innovation performance. To some extent these differences in empirical evidence can be explained through differences in methodology, sampling, the indicator employed to measure innovation or the stage of the innovation process (e.g. Carayannis et al., 2016; Fodi et al., 2013). Even when the methodology is similar (such as DEA - Data Envelopment Analysis or SFA - Stochastic Frontier Approach) if the examined period and set of countries are different it is not possible to have completely comparable results, given the relative nature of DEA or SFA efficiency scores. Thus, these previous studies should not be considered as a validation effort, but rather as a reference for comparing efficiency estimates (e.g. Guan and Chen, 2010).

Finally, whilst there are a number of factors that determine the efficiency of a national or regional innovation system, one of the most important is the level and quality of interaction between the various economic agents and system elements, which is the backbone of the innovations system itself (e.g. Nelson and Rosenberg, 1993; Asheim and Coenen, 2006; Cooke, 1992, 2008). Hajek et al. (2013) found that European regions with more human resources in science and technology have higher levels of cooperation, which is also influenced by the level of higher education and the type of business activity. Besides the interactions between agents, other factors have been identified as important determinants of system performance, such as the presence of high R&D, the technological proximity between R&D activities by public and private institutions (Slavtchev, 2011), and population density (Fritsch and Slavtchev, 2011).

Looking at Portuguese regional innovation systems, studies indicate the existence of some shortcomings related to the systems' innovation capacity. These weaknesses are mostly related to the reduced interaction between the regional system agents (Santos, 2000; Santos and Simões, 2014; Oliveira and Natário, 2016). Hierarchical organizational structures of institutions, lack of coordination between innovation policies, and low quality of infrastructures supporting innovation (Santos and Simões, 2014) are also at fault for the observed lack of interactions. These authors (Natário et al., 2012; Oliveira and Natário, 2016; Santos, 2000; Santos and Simões, 2014) argue that the policies implemented so far have led to lack of competitiveness, increased disparities between regions, and did not allow for innovation capacity and knowledge production to improve. Therefore, based on the Portuguese case, the assessment of the role of agents' interactions in determining regions' innovation efficiency seems to be an important step to understand the performance of regional innovation system in the EU context.

Methodology

Econometric approach

The literature on the measurement of regional innovation performance has been dominated by the production possibility set (e.g. Broekel et al., 2018; Chen and Guan, 2012; Fritsch and Slavtchev, 2011; Kalapouti et al., 2017; Zabala-Iturrigagoitia et al., 2007). This means that regional innovation systems´ performance is measured in terms of their efficiency, where efficiency corresponds to the concept of technical efficiency as introduced by Farrell (1957). Following Farrell (1957) technical efficiency of the ith-productive unit is defined by the ratio of the observed output for the ith-productive unit relative to the potential output defined by a frontier. Therefore, the production frontier function allows to identify a frontier that is defined as the maximum attainable output by a given level of inputs, and it is based on the idea that economic agents cannot exceed this frontier. Therefore, the frontier function is a methodology that evaluates the efficiency of a unit compared to other homogeneous units.

Following Jaffe (1986), we will assume a Cobb-Douglas type knowledge production function (KPF) for the relationship between output and inputs. The knowledge production function is defined as a production function, but augmented with the inputs associated with knowledge, traditionally R&D activities. To estimate region´s innovation efficiency and evaluate the impact of agents´ interactions on this efficiency we apply a stochastic frontier approach (SFA). This means that the stochastic component of the production function is modelled with a two-part error structure (Aigner et al. 1977; Meeusen and van den Broeck 1977). SFA key advantages are that it can overcome the impact of statistical noise and random environment factors on efficiency measures and avoids a problem of endogeneity of the regressors in the second step and the inconsistency of the estimator by using a simultaneous estimation of the models production function and efficiency equation (Faria, 2005; Kumbhakar and Lovell, 2000).[1]

So, our SFA model is defined as:

$$y_i = \alpha + x_i' \beta + v_i - u_i \qquad i = 1, \dots, N \tag{1}$$
$$\text{where } v_i \sim N(0, \sigma_v) \quad u_i \sim N^+\left(0, \sigma_{u_i}\right), \text{ and}$$

[1] Two methods can be used to measure efficiency, a deterministic one - Data Envelopment Analysis (DEA, or a stochastic one - Stochastic Frontier Analysis (SFA). DEA has been found more competent in analysis of multi-output scenarios (e.g. Guan and Chen, 2010, 2012), with the additional advantage of not imposing an explicit functional form for the underlying technology and an explicit distributional assumption for the inefficiency term. Yet, it has de cost of not controlling for unobserved factors and statistical noise.

$$u_i = z_i' \varphi \tag{2}$$

where y_i represents the logarithm of the product of the productive unit; x_i' corresponds to the vector of production factors; β is the vector of parameters related to technology; v_i is a normal, independent and identically distributed disturbance capturing random departures from the predicted-by-the-model output (due to unobserved observation-specific random shocks, measurement errors, etc.); u_i is a realization from a half-normal, independent and identically distributed term capturing deviations from the frontier caused by a suboptimal input usage, namely R&D inefficiency (Fu and Yang, 2009; Wang, 2007), z_i' is a vector of exogenous variables (including a constant term) and φ is the vector of unknown parameters to be estimated (the so-called inefficiency effects). Thus, the term u_i corresponds to inefficiency, the greater the u_i the greater the inefficiency. It should be noted that v_i and u_i are independent of each other and independent.

Data and empirical variables

Our main data source is the Regional Innovation Scoreboard developed by the European Commission (EC, 2014), which contains information on 18 indicators of innovation in 220 European regions at NUTS II level. The data have been normalized in [0,1] which helps to overcome differences in measurement across EU countries[2] making the database a widely used tool in similar analysis (e.g. Carayannis et al., 2016; Edquist and Zabala-Iturriagagoitia, 2015; Fodi and Usai, 2013; Fodi et al., 2013). From this database we collected data on the production function inputs, as well as data on the determinants of efficiency. The second source of data is the Eurostat Regional Statistics, from which we collected data on Gross Domestic Product (GDP) and population by region.

An important issue to consider is the choice of variables that should enter into the knowledge production function. We followed previous studies (e.g. Capello and Lenzi, 2013b; Fodi et al., 2013; Kaihua and Mingting, 2014; Zabala-Iturriaggoitia et al., 2007) and measured output by GDP per capita. GDP can be considered a performance indicator since the main objectives of a regional innovation system are to increase competitiveness and social welfare. GDP per capita also measures the level of development in a given area (city, region, country) and, for this reason, the production of innovation of a region also leads to productivity growth and, consequently, to its development. Also, a global measure such as GDP is more appropriate to our case since we are not investigating the innovation process phases – knowledge production and knowledge commercialization, separately.

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[2] See EC (2014) for a description of the normalization procedure.

As inputs, we considered the traditional inputs of a production function labour and capital and added the knowledge inputs *R&D*, *Patents* and *Citations*. The RIS indicators that we use as proxies for these inputs are as follows. Labour was measured by the variables *Education* and *Training*, which represent the advanced skills resources that are fundamental for the innovation process and the lifelong learning process, respectively. The input capital measures differences in the productive specialization of the regions. On way to measure it is by looking at the composition of industries at regional level. In particular, regions with a high proportion of medium to high technology intensive industries would be more endowed in capital. Therefore, the input capital was proxied by the relative importance of medium to high technology intensive industries in the region in terms of employment. The knowledge input is measured by the variables *R&D, Patents* and *Citations.* R&D expenditure is one of the major determinants of economic growth in a knowledge-based economy. For this reason, R&D expenditures are a key indicator that demonstrates the future competitiveness, wealth and growth of a particular region and are also essential for the occurrence of improvements in the production of technologies. Additionally, R&D is essential for the development of formal knowledge in firms. The variable *Citations* is a measure of the stock of knowledge where it is assumed that the most cited publications present a higher quality, we also use *Patents*. Patents can be seen as an input or an output of the knowledge production function as discussed by Griliches (1990:296-297). Given that the output measure relates both processes – knowledge production and knowledge commercialization -, we also include patents as an input of our production function. It provides an estimate of the contribution of knowledge to productivity change at the regional level.

For the analysis of the role of interactions among agents in determining the technical efficiency of regional innovation systems, we include two explanatory variables in the inefficiency equation, namely *Copublications* between private and public agents, which measures the interactions between public and private research and active collaboration activities between researchers in the business sector and the public sector, resulting in academic publications, and *Collaboration* that measures the degree of involvement of Small and Medium Enterprises (SMEs) in cooperation activities in innovation. This last variable measures the knowledge flows between research institutions and firms.

Another issue to consider in the estimation of the knowledge production function is the time period to which input and output relate. Specifically, the idea is that output takes some time to emerge, i.e. there is a time lag. The literature suggests a time lag of one or two years (Griliches, 1990; Capello and Lenzi, 2013b; Carayannis et al., 2016; Fodi and Usai, 2013; Fodi et al., 2013). Thus, the input variables are lagged by one or two years, depending on data availability. It should be noted that the RIS indicators are mostly bi-annual. Finally, regarding the period of analysis, we defined the years 2012 and 2015 given that the most recent GDP data are relative to 2015. Due to data availability limitations our final database comprises 206 regions and 23 countries.[3].

Empirical variables, their acronyms and description is presented in Appendix A1, while Table 2 shows the descriptive statistics of the variables used to estimate the production function and the (in)efficiency equation in 2012 and 2015.

INSERT TABLE 2 HERE

We may observe that all mean values of the inputs and output have increased between 2012 and 2015, with the increase being more pronounced in the inputs than in the *GDP* per capita. On the other hand, the variables accounting for economic agent´s interactions, *Copublications* and *Collaboration*, have stagnated or even decreased during the observed period. This may suggest that these determinants of efficiency could be quite hard to change, imposing a significant hurdle to obtain efficiency gains.

[3] In the case of Portugal only 5 regions were included in the analysis (Norte, Centro, Lisbon, Alentejo and Algarve); Autonomous Regions of Madeira and the Açores were excluded due to lack of data.

Results

Here, empirical results on the determinants of regions' innovation efficiency, the geographical distribution of regional efficiency scores and its linkage with regional innovation systems are presented and discussed.

On the determinants of regional innovation efficiency

Based on the knowledge frontier production function for EU regions (see, equations (1) and (2)) Table 3 presents the estimates of the factors influencing regional innovation efficiency. Overall, the estimates indicate that regions with large percentage of educated and skilled population and high share of technology intensive firms are more productive, corroborating that resources are a crucial factor for economic performance.

INSERT TABLE 3 HERE

Interestingly, by comparing the two periods, education seems to lose power in explaining performance differentials at regional level, suggesting that the concentration of top-educated employees at regional level could not guarantee high performance. Moreover, the stock of people undergoing long-life training has a higher elasticity than the stock of people with a higher education. This supports previous works showing that informal knowledge embedded in human capital are key to regional growth (Asheim and Coenen, 2006; Capello and Lenzi, 2014; Hajek et al., 2014) and may actually have an equally important or greater impact on regional output than formal knowledge (Capello and Lenzi, 2014, 2015; Fodi et al., 2013).

In turn, looking at the production factors associated with knowledge, the non-significance of R&D seems to be the most unexpected result as it suggests that, holding everything else constant, R&D expenses have no impact on production at regional level. Even so, a possible explanation is that the variability of R&D effectiveness on regional output depends on the allocation of R&D among firms' types and firms' capability to convert R&D expenses on higher production. Rather than looking at total R&D expenses, it would be more informative to take into account its distribution among firms in order to evaluate the innovation system efficiency.

Nonetheless, the estimates disclose the importance of scientific knowledge, measured by the input *Citations*, in explaining production at regional level. Whereas *R&D* includes both commercialized and non-commercialized formal knowledge, *Citations* are more related to scientific knowledge hence non-commercialized knowledge. As such, the larger importance of *Citations* relative to *R&D* suggests that fundamental scientific knowledge is having a positive and larger effect on regional output than applied scientific knowledge. Jointly, the estimates indicate that the determinants related to knowledge impact positively on regional efficiency.

In the efficiency equation we treat the amount of interactions among economic agents as the key determinants of efficiency. The negative coefficient in *Copublications* and *Collaboration* implies that these interactions decrease the variance of the inefficiency distribution, in other words increase efficiency. As expected, these results provide support to the notion that interactions among the agents are important determinants of the innovation system efficiency as largely claimed (e.g. Asheim e Gertler, 2005; Camagni e Capello, 2013; Cooke, 1992, 2008; Fritsch e Slavtchev, 2011; Tödtling e Trippl, 2005). Furthermore, the estimates also suggest that *Copublications*, which account for scientific interactions, seem to have a stronger effect than *Collaborations*, which account for firms´ collaboration. We see these results as corroborating evidence for the findings by Breschi and Lenzi (2015, 2016) and Moreno and Miguélez (2012) in which external sources of knowledge have a positive effect on the region´s innovative capability, namely that inventors´ mobility has been found fundamental to the regions innovative capacity (Capello and Lenzi, 2019). As a result, improvements on scientific interactions and firms' collaboration would render significant efficiency gains. It is an important finding that should help policymakers to design innovation policies at regional level.

Linking efficiency to regional innovation systems

Another important issue to examine it is whether there is a clear relationship between efficiency at regional level and regional innovation systems types. Table 4 presents t-tests on mean efficiency differences among EU regions following the Regional Innovation Scoreboard taxonomy. First, we observe that the EU mean efficiency is high in both periods, 0.88 and 0.89 indicating that, on average, regions are clustered near the frontier, which corresponds to the most common assumption in the technical efficiency literature (see Schmidt and Lin, 1984); a similar result has been found in previous studies as well (e.g. Fristch and Slavtchev, 2011). On the other hand, mean technical efficiency slightly increases from 2012 to 2015 and, simultaneously, standard deviation slightly decreases suggesting some catching-up in the innovation process among EU regions. Using a different approach, Fodai and Usai (2013) obtain a similar finding for 271 EU regions over the period 2000-2007. In particular, they report a reduction of the technology gap by Eastern regions with respect to Western regions.

INSERT TABLE 4 HERE

Diving the sample according to the Regional Innovation Scoreboard taxonomy, the t-tests of mean differences show that regions with more resources, *Innovation Leaders* and *Strong Innovators*, are also the most efficient ones with efficiency levels of 0.94 and 0.92 in the two sample years. *Moderate Innovators* and *Low Innovators* regions lag well behind the former two groups, with a mean efficiency of 0.81 and 0.83 in 2012 and 2015, respectively. Therefore, this result is largely consistent with a core-periphery pattern of innovation efficiency distribution (Fodi and Usai, 2013; Fodi et al., 2013; Fritsch and Slavtchev, 2011).

But, more interestingly, one novelty of our findings is that the core-periphery pattern does not seem to be at work in the *Low Innovator* regions. Regions belonging to the *Low Innovator* group exhibit slightly higher efficiency levels than regions in the *Moderate Innovators* group. Whereas this last result corroborates the argument that regions with less endowments can be as efficient as or even more efficient than other larger and richer regions (Zabala-Iturriagaoitia et al., 2007), it only seems to apply to regions with medium levels of resources. Given that in the Low innovators group are mostly Eastern regions, this result corroborates Fodi and Usai (2013) findings in which Eastern regions have been able to close the efficiency gap with respect to Western regions, where most *Moderate Innovators* regions are located. Moreover, there seems to be more turmoil among the low resources endowments regions than in the high resources endowments ones, suggesting that in those regions the catching-up process could not be uniformly in action. If so, these regions require a deeper examination in order to disclose their specificities and factors that may restrain the catching-up process in some regions. Portuguese regions, which are classified as *Moderate Innovators*, exhibit a mean efficiency well above its group.

Given the one dimension nature of the Regional Innovation Scoreboard, each group within the RIS taxonomy may contain very differentiated sub-territories that are difficult to classify according to this taxonomy (Capello and Lenzi, 2013a; Moreno and Miguélez, 2012). Therefore, an alternative taxonomy of innovative regions is applied to examine the link between efficiency and regions' innovative types.

Table 5 presents mean efficiency at regional level based on Capello and Lenzi (2013a) taxonomy of innovative regions. Some interesting results emerge from this analysis. First, Science Based regions are the most efficient in the use of their resources in both time periods, which is consistent with previous evidence. For instance, Capello and Lenzi (2015) found that regional innovation patterns based on local scientific knowledge-creation processes have positive returns to scientific knowledge, and Carayannis et al. (2016) found that European regions are more efficient in producing knowledge than commercializing it.

INSERT TABLE 5 HERE

Second, there are no statistically significant differences, on average, in efficiency across regions with different innovation modes, except for the case of *Science Based* regions. This is a novelty of our results, which are opposite to previous results (Capello and Lenzi, 2015; Fodi et al., 2013) suggesting that different modes of doing innovation could render similar efficiency scores even if the regions have dissimilar input endowments. Our results, show a clear divide between Science Based regions and the remaining types. This evidence helps to conciliate opposite results regarding which regions are more efficient in using their resources. Thus, the ´more is better´ view applies to regions whose innovation mode is based on science: these European regions are clearly more efficient than their counterparts in using their resources. However, this view does not apply to the remaining regions, where different innovation modes seems no yield, on average, differences in efficiency and, simultaneously it is also possible to have good performers among less endowed regions. Hence, these results corroborate the notion that being innovative is different from being efficient in transforming inputs into outputs or than having large amounts of resources (e.g. Capello and Lenzi, 2013b, Nasierowski and Arcelus, 2012, Matei and Aleda, 2012; Zabala-Iturriagagoitia et al., 2007). The mode of doing innovation seems to be a crucial factor driving efficiency at regional level.

Looking at the particular case of Portugal - see Table 6 - the results highlight that within a country there are also different modes of innovation as among the five Portuguese regions we found four types of regions. Interestingly, the richer region in the country – Lisbon – also has the highest efficiency score among Portuguese regions and also scores slightly above its European counterparts, the *Smart Technological Application* regions group. Furthermore, there is some variability on innovation modes, which appears to affect efficiency. The higher score of Lisbon – a Smart Technological Application region – is consistent with other findings, which found that this type of region is the second most efficient (Fodi et al., 2013). The arguments justifying the high efficiency of Lisbon are based on the fact that here are concentrated the main economic and political institutions of the country, the largest companies and financial groups in Portugal, and a large number of scientific and technological research institutes. As a consequence, the workforce in this region is highly qualified and has more external higher levels of cooperation, namely external (Almeida et al., 2011).

INSERT TABLE 6 HERE

The other Portuguese regions score below their European counterparts, however, the observed variability in terms of efficiency reinforce the argument that resource and innovation modes that take place in the region are equally relevant to explain efficiency differentials in the innovation process. It is interesting to note that the Portuguese regions doing innovation classified as *Applied Science* and *Imitative Innovation* are those attaining higher efficiency gains over the 2012-2015 period, starting an expressive convergence process to EU mean. This finding appears to indicate that, in the Portuguese case, those modes of doing innovation could be the most suitable to the Portuguese specific economic characteristics.

Among the EU regions, Table 7 shows the top-5 and the bottom-5 regions in terms of efficiency in order to examine whether there is a clear cut-off higher and lower performers. Clearly, following the Regional Innovation Scoreboard classification, the most efficient regions are located in *Innovation Leader* and *Strong Innovator* regions, whereas the least efficient are in Low Innovator regions. This illustrates a clear divide among EU regions in which efficiency in the use of resources appears to be mainly associated with their availability.

INSERT TABLE 7 HERE

To some extent, a similar result emerges from the efficiency rank according to Capello and Lenzi (2013a) but there is more divergence, in which the same type of innovations region could generate higher performers - Top-5 regions - or lower performers - Bottom-5 regions. Among the bottom-5 appears the Imitative type of innovation region, that is, regions which tend to innovate mostly through replication. Yet, among the top-5 regions we find mostly *Smart and Creative Diversification* and *Applied Science* type of innovation regions, but not the *Science Based* type of innovation region. Whereas, the *Science Based* regions have on average higher efficiency, highlighting the importance of scientific knowledge to innovation and economic performance, there are capabilities in the use of resources that are to some extent independent to the innovation type or process that takes place in the region and which allows each individual region to be more or less efficient in the process.

Conclusions

This paper was motivated by some conflicting views and findings as to which type of region is more innovative and efficient in using its resources. In order to investigate regional innovation efficiency, we assessed the role of interactions among economic agents on determining the level of efficiency and investigated the efficiency distribution across European regions. Our findings show that technical efficiency is significantly driven by knowledge interactions among economic agents and provide noteworthy insights into the distribution of efficiency scores across different types of regional innovation systems.

From a resource-based perspective (Regional Innovation Scoreboard taxonomy) our findings provide some support to the core-periphery divide among European regions with a clear gap between *Innovation Leaders* and *Strong Innovators*, located in northern and centre Europe, vis-à-vis *Moderate* and *Low Innovators*, located in peripheric regions. However, less endowed regions, those usually classified as *Moderate Innovators* or *Low Innovators*, challenge the core-periphery divide, as some regions with fewer resources devoted to innovation appear to achieve higher efficiency than regions with more resources. Therefore, the argument that the most efficient regions are not necessarily the ones with more resources seems to be particularly valid in the case of less endowed regions. So, from a policy point of view our findings suggest that investment in technological inputs is important but there may be other policy avenues to pursue in order to obtain innovation and efficiency gains at regional level.

Two novelties of our findings are that the most efficient regions in using their resources, on average, are those innovating through formal knowledge (*Science Based* regions) and that efficiency differentials among regions with different modes of doing innovation are only significant between the *Science Based* and the other region types. In other words, we do not observe efficiency differentials among different modes of doing innovation, except in the *Science Based* regions indicating that the mode of doing innovation could be a crucial explanatory factor of innovation efficiency at regional level. This result is consistent with previous evidence (e.g. Carayannis et al., 2016) that found that European regions are, on average, more efficient in knowledge production than in knowledge commercialization.

In this regard, our findings largely support Capello and Lenzi´s (2013a, 2013b) claim that efficiency in taking advantage does not link to the strength of local knowledge. Yet, this link seems to be present in the case of regions that innovate through science, hence largely rely on formal knowledge. In terms of policy recommendations, our results are in line with the literature as they also support the idea that regional policy should be specific to the region´s innovation capabilities.

Looking at Portuguese regional innovation systems, they appear to perform slightly below the average of their EU counterparts – except for the Lisbon region, suggesting that public policies, over the last three decades, investing in different types of knowledge – formal as well as informal -, and technological inputs do not boost efficiency convergence towards EU average. Lisbon is both the richest and most efficient Portuguese region indicating the importance of access to knowledge resources and other innovation inputs that are present in that metropolitan region. In particular, Lisbon seems to be taking some advantage of the higher intensity in resources and cooperation among economic agents. However, the mode of doing innovation appears to prevent the region to be a higher performer in the EU context. As such, understanding the constraints in adopting a mode of doing innovation that would yield higher performance would be a very rewarding avenue of further research. Another interesting avenue of further research would be to assess whether public regional policies are more prone to favour technological inputs endowments than a more cohesive innovation system able to challenge the mode of doing innovation and, hence, to obtain efficiency gains.

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Table 1: Empirical evidence of regional innovation efficiency.

Authors	Data	Indicator	Methodology	Best performer	Location	Region type
Capello and Lenzi, 2013b	Regional (EU)	GDP	Regression	Medium knowledge endowments	Central and Northern Europe Northern Spain and Madrid, Northern Italy, Czech Republic.	Smart tech
Carayannis et al. 2016	National (EU)	Multi-output	DEA	Some of the richest (some mixed cases)	Central, Northern Europe	
	Regional (EU)	Multi-output	DEA	Richest and less developed	Central (Germany), Southern Europe (Portugal)	
Fodi et al., 2013	Regional (EU)	Patents	Regression	Richest	Central, Northern Europe, clusters	Science-Based & Applied Science
			DEA	Richest		
		GDP	Regression	Richest	Central, Northern Europe, specific clusters	Science-Based & Applied Science
			DEA	Less developed	Southern, Eastern Europe	Imitative, Smart tech
Fritsch and Slavtchev, 2011	Regional (Germany)	Patents	DEA	Richest, knowledge intensive	Centre Germany	Metropolitan
			SFA	Richest, knowledge intensive	Centre Germany	Metropolitan

Zaballa-Iturriagagoitia et al., 2007	Regional (EU)	Patents	Index	Richest	Central, Northern Europe	
			DEA	Less developed	Southern Europe	
	Regional (Spanish)		Index	Richer and medium	Madrid	Metropolitan
		Patents	DEA	Less developed	Navarra, Basque Country, Balearic Islands, Castilla la Mancha	Peripheric

Table 2. Descriptive statistics of empirical variables, EU NUTS2 regions, *N = 206*.

	Variable	2012 Mean (Std. Dev.)	2012 Min., Max.	2015 Mean (Std. Dev.)	2015 Min., Max.
Production function					
Output	*GDP per capita*	0.026 (0.014)	0.004, 0.082	0.028 (0.014)	0.005, 0.078
Inputs	*R&D stock*	0.396 (0.159)	0.105, 0.965	0.414 (0.151)	0.071, 0.944
	Citations	0.591 (0.174)	0.109, 0.919	0.608 (0.162)	0.091, 0.927
	Patents	0.310 (0.116)	0.030, 0.613	0.324 (0.104)	0.057, 0.542
	Training	0.409 (0.208)	0.021, 1	0.428 (0.216)	0.022, 1
	Education	0.446 (0.186)	0.050, 0.928	0.480 (0.181)	0.119, 0.985
	Capital	0.484 (0.167)	0.118, 1	0.490 (0.160)	0.147, 0.971
Inefficiency equation					
	Copublications	0.291 (0.163)	0.025, 0.855	0.280 (0.163)	0.018, 0.822
	Collaboration	0.350 (0.200)	0.012, 0.861	0.350 (0.209)	0.005, 1

Table 3. Estimates of stochastic production function and technical efficiency in the EU NUTS2 regions, 2012 and 2015.

	2012	**2015**
Production function parameters[a]		
R&D stock	-0.022	0.049
	(0.079)	(0.071)
Patents	-0.111	-0.003
	(0.092)	(0.086)
Citations	0.681***	0.596***
	(0.107)	(0.111)
Training	0.187***	0.242***
	(0.063)	(0.055)
Education	0.144**	0.058
	(0.058)	(0.063)
Capital	0.387***	0.418***
	(0.093)	(0.069)
Technical inefficiency equation[b]		
Copublications	-0.994**	-0.622**
	(0.390)	(0.260)
Collaboration	0.039	-0.433*
	(0.285)	(0.261)
Region dummies	Yes	Yes
Constant	-2.783***	-2.625***
	(0.143)	(0.091)
Wald test	109.16***	138.79***
Log-likelihood	-33.355	-14.338
Obs.	206	206

Notes: [a] Dependent variable is GDP per capital; [b] dependent variable is technical inefficiency $\ln(\sigma^2_{u\,i})$ estimated from production function; the negative sign in *Copublications* and *Collaboration* coefficients should be interpreted as a positive effect on efficiency since the dependent variable is inefficiency; robust standard errors clustered in the regions in parenthesis. Means significant at the 1% ***, 5% **, 10% * level. Wald test of coefficients´ overall significance.

Table 4. Technical efficiency by Regional Innovation Scoreboard group, EU and Portugal NUTS2, 2012 and 2015.

Region group[a]	**Innovation Leader** **N=47**	**Strong Innovator** **N=59**	**Moderate Innovator** **N=12**	**Low Innovator** **N=88**	**Portugal** **N=5**	**EU** **N=206**
2012	0.941 (0.021)	0.923 (0.020)	0.812 (0.065)	0.831 (0.122)	0.845 (0.044)	0.881 (0.097)
T-test of mean difference	_	> ***	> ***	< ***	_	
T-test of mean difference of Portugal *vs.* Moderate Innovator regions group	_	_	_	_	> *	
2015	0.943 (0.014)	0.927 (0.022)	0.804 (0.068)	0.849 (0.110)	0.866 (0.029)	0.890 (0.088)
T-test of mean difference	_	> ***	> ***	< ***	_	
T-test of mean difference of Portugal *vs.* Moderate Innovator regions group	_	_	_	_	> ***	

Notes: Mean values, standard deviation in parenthesis; values refer to technical inefficiency thus lower values mean more efficiency. [a] Region group refers to the RIS classification of EU regions regarding their position in the Innovation Index, i.e., Innovation Leader, Strong Innovator, Moderate Innovator, Low Innovator; Portuguese regions are Moderate Innovators. T-test of mean differences *** significant at 1% level.

Table 5. Technical efficiency by innovative region type, EU NUTS2, 2012 and 2015.

Innovative region type[a]	**2012**			**2015**		
	Mean	Mean	T-test	Mean	Mean	T-test
Science Based *vs.* Applied Science	0.909	0.885	>***	0.918	0.875	>***
	(0.059)	(0.081)		(0.045)	(0.108)	
Applied Science *vs.* Smart Technological Application	0.885	0.886	n.s	0.875	0.890	n.s
	(0.081)	(0.099)		(0.108)	(0.096)	
Smart Technological Application *vs.* Smart and Creative Diversification	0.886	0.875	n.s.	0.890	0.890	n.s.
	(0.099)	(0.108)		(0.096)	(0.081)	
Smart and Creative Diversification *vs.* Imitative Innovation	0.875	0.870	n.s.	0.890	0.893	n.s.
	(0.108)	(0.110)		(0.081)	(0.086)	

Notes: [a] Capello and Lenzi´s (2013a) taxonomy of innovative region; Mean values of technical inefficiency, standard deviation in parenthesis; lower values mean more efficiency. T-test of mean differences *** significant at 1% level, n.s. = not significant. Science Based *N*=20, Applied Science *N*=46, Smart Technological Application *N*=28, Smart and Creative Diversification *N*=78, Imitative Innovation *N*=33.

Table 6. Technical efficiency by innovative region type, Portugal, 2012 and 2015.

	Portugal			EU[b]	
Innovative region type[a]	NUTS2 Region	2012	2015	2012	2015
Applied Science	Norte	0.794	0.818	0.885	0.875
Smart Technological Application	Lisboa	0.887	0.893	0.886	0.890
Smart and Creative Diversification	Alentejo	0.871	0.863	0.875	0.890
Imitative Innovation	Centro	0.870	0.871	0.870	0.893
	Algarve	0.801	0.883		

Notes: [a] Capello and Lenzi´s (2013a) taxonomy of innovative region; lower values mean more efficiency; [b] mean values. Science Based *N*=20, Applied Science *N*=46, Smart Technological Application *N*=28, Smart and Creative Diversification *N*=78, Imitative Innovation *N*=33.

Table 7. Top-5 and bottom-5 efficient regions, EU NUTS2, 2012 and 2015 ($N = 206$).

	Panel A		Top-5 Regions				
	Efficiency				**Efficiency**		
NUTS2	**2012**	**(1)**	**(2)**	**NUTS2**	**2015**	**(1)**	**(2)**
Trøndelag (NO)	0.985	Innovation Leader	Smart and creative diversification	Région de Bruxelles (BE)	0.966	Strong Innovator	Applied Science
Hovedstaden (DK)	0.982	Innovation Leader	Applied Science	Oslo og Akershus (NO)	0.9640	Innovation Leader	Applied Science
Groningen (NL)	0.966			Hovedstaden (DK)	0.963		
Région de Bruxelles (BE)	0.962	Strong Innovator	Applied Science	Trøndelag (NO)	0.963	Innovation Leader	Smart and creative diversification
Stockholm (SE)	0.961	Innovation Leader	Smart and creative diversification	Hamburg (DE)	0.962	Innovation Leader	Smart and creative diversification

Table 7. Top-5 and bottom-5 efficient regions, EU NUTS2, 2012 and 2015 ($N = 206$).

		Panel B	**Bottom-5 Regions**				
	Efficiency				**Efficiency**		
NUTS2	**2012**	**(1)**	**(2)**	**NUTS2**	**2015**	**(1)**	**(2)**
Severna i yugoiztochna (BG)	0.537	Low Innovator	Applied Science	Észak-Alföld (HU)	0.607	Low Innovator	Smart and creative diversification
Közép-Dunántúl (HU)	0.524	Low Innovator	Smart and creative diversification	Lubuskie (PL)	0.513	Low Innovator	Smart tech
Észak-Magyarország (HU)	0.483	Low Innovator	Imitative	Swietokrzyskie (PL)	0.507	Low Innovator	Imitative
Nord-Est (RO)	0.483	Low Innovator	Smart tech	Opolskie (PL)	0.453	Low Innovator	Smart and creative diversification
Sud-Muntenia (RO)	0.306	Low Innovator	Smart and creative diversification	Severna i yugoiztochna (BG)	0.331	Low Innovator	Applied Science

Notes: Columns (1) and (2) refer to the Regional Innovation Scoreboard and Capello and Lenzi (2013a) taxonomies, respectively.

APPENDIX A1. Empirical variables

Variable	Description
GDP	Gross Domestic Product *per capita* in region *i*, 2012 and 2015.
R&D stock	Private and public sector expense in R&D as a percentage of GDP in region *i*, 2010 and 2014.
Patents	Patents count per million of inhabitants in region *i*, 2010 and 2014.
Citations	Scientific publications in the top-10 most cited publications as a percentage of the total number of scientific publications in region *i*, 2010 and 2014.
Training	Percentage of population between 25 and 64 years of age that took part in training activities, in the total population in that age group, in region *i*, 2001 and 2013.
Education	Percentage of population between 30 and 34 years of age with a college degree, in the total population in that age group, in region *i*, 2011 and 2013.
Capital	Percentage of jobs in sectors classified as technology intensive, in manufacturing and services, in the total number of jobs in region *i*, 2011 and 2013.
Copublications	Public-private co-publications per million population in region *i*, 2011 and 2013.
Collaboration	Innovative SMEs collaborating with others as percentage of SMEs, in region *i*, 2010 and 2014.