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The contribution of university, private and public sector resources to Italian regional innovation system (in)efficiency

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Abstract

This paper investigates the regional innovation system (RIS) efficiency, and its determinants, in Italy through a Stochastic Frontier Analysis and using the concept of a knowledge production function. The contribution of university, private and public sector resources devoted to research and development (R&D), in generating innovation, has been examined, as well as the impact of several exogenous environmental variables on RIS efficiency. The empirical findings are in favour of the importance of R&D investments taking place in the universities and in the private sector, which benefit the most to regional innovation activities; the evidence also suggest the relevance of the knowledge context in which the firms operate as the existence of an intermediation structure, such as a university technology transfer office, has an important role on the innovation process. State-level policies can be detrimental for overall efficiency, and instead special interventions for regions in the Southern regions should be designed.

Keywords: Regional innovation system, Technical efficiency. Knowledge production function

JEL-Codes: O31; C14; C67; R12

1. Introduction

Research and development (R&D) activities, likewise patents, could be considered as new ideas and pieces of knowledge that may turn into innovation when commercially exploited (Schumpeter, 1934; 1942); thus, innovation may be seen as the ability to use such knowledge to generate, develop and improve new products, processes and services. Generally speaking, there are different forms of innovation: (i) the introduction of new ways of doing things (Porter, 1990); (ii) the ability to use resources to create value (Drucker, 1993); (iii) the commercial exploitation of an idea (UK Department of Trade and Industry Innovation, 1994) and (iv) the output of a research and development process (Tidd, et al. 1997). However, regardless of the meaning of innovation adopted in the literature, it is still debated by the researchers why a system should innovate and what are the related benefits of maintaining innovation activities. Indeed, many are the factors involved in the innovation process such as economic (growth, competitiveness, internationalization), social (human capital development, employment and entrepreneurship), business (improvement of performance, value creation, competitive advantage) and scientific (development and enhancement of the knowledge). It is, instead, more clear that innovation is fundamental to economic growth of a region which, as a consequence, may increase technological capital by innovating; knowledge and technological progress are, indeed, among the main engines of economic dynamics in most endogenous growth models (Romer, 1990). In other words, advantages of regions, in terms of innovation outputs, could be also related to the ability of regional firms to develop their innovation (Krugman, 1991; Maskell and Malberg, 1999). Thus, it is especially important to find out what components of an R&D system are most decisive as engines of innovation and what are the factors determining systems' innovatory capacities. See Capello and Lenzi (2014) for more details on the role played by knowledge and innovation as drivers of regional economic growth and on their spatial impact and McCann and Simonen (2005) for the role played by geography in the promotion of innovation.

An important empirical approach to analyse the process of innovation creation is the knowledge production function (KPF), originally formalized by Griliches (1979) and Pakes and Griliches (1984), showing that knowledge is mainly generated through R&D activities carried out by firms, universities and other research institutions (see Acs et al. 2002). Both knowledge creation and regional innovation through research and technology transfer represent relevant channels. Promoting enterprise, business development and growth, all activities linked to the possibility of busting a more entrepreneurial culture and a more favourable business environment, also have to be considered. Empirical evidence from firm surveys (Mansfield, 1995; 1997; Cohen et al. 2002; Veugelers and Cassiman, 2005) confirms the importance of university research for corporate innovation performances. Knowledge transfers from academia have been investigated through licensing and academic spin-off activities (Shane, 2002) and citation to academic patents (Henderson et al. 1998).

See Maietta (2015), on the channels through which university–firm R&D collaboration impacts upon firm product and process innovations, and Caniëls and van den Bosch (2010), on the role of higher education institutions (HEIs) in building regional innovation systems. In the literature, KPF has been implemented at regional level (see among others Crescenzi, 2005; Rodrıguez-Pose and Crescenzi, 2008; Sterlacchini, 2008; Marrocu, Paci, and Usai, 2013) showing evidence of the key role of knowledge inputs (i.e. R&D expenditures or employees) in generating knowledge outputs (i.e. patents).

The purpose of the paper is main-fold. Firstly, we investigate the production of knowledge of a regional innovation system (RIS), by estimating a RIS technical efficiency based on the concept of a knowledge production function as suggested by Griliches (1979) and Jaffe (1989) in the Italian regional context; in order to study the relationship between inputs and outputs of the innovation process, we use a Stochastic Frontier Analysis (SFA), which has been widely used to study technical efficiency in various settings since its introduction by Aigner et al. (1977), and Meeusen and van den Broeck (1977). The approach used in the paper provides, to the best of our knowledge, a first attempt to measure the contribution of investment in R&D (expenditures and employees) on an innovative output measure such as the number of patents, in Italy, taking into account different sectors. Specifically, we address the following research question: does the contribution of university, private and public sector resources to Italian regional innovation system (in)efficiency differ? In order to address this issue, we specifically rely on highly disaggregated proxies for measuring the inputs to the innovation process such as the expenditure and the staff employed in R&D activities in the public sector, in the universities and in the private sector (see Section 3.1. for more details on the production set). This allows us to better analyse the factors that have a direct impact on innovation outputs (as measured by registered patents). The capacity of generating local knowledge, and of turning knowledge into growth, has long been identified with the presence of territorial conditions in the area. Therefore, secondly, this paper directly investigates whether RIS efficiency is influenced by some exogenous characteristics of the regional environment - i.e. labour market and industries' characteristics - (see Sections 2 and 3.2 for more details on the way these variables are included into an SFA single stage approach); indeed, failing to model the exogenous factors leads to bias estimation of the technical efficiency scores (e.g. Caudill and Ford 1993; Caudill et al. 1995; Hadri 1999; Wang 2003). More specifically, we look at the effect of variables like a measure of urbanization such as the density of the population, a control for the capability of technology transmission proxied by the existence of an intermediation structure, such as universities' technology transfer offices, and some indicators of the labour market structure and of the industries' characteristics such as the rate of unemployment, a control for employment in services and in industry sectors and the involvement of firms in export activities. In other words, we explore whether the environmental channel can explain regional differences in term of diffusion of knowledge and innovation.

To anticipate the results, we show evidence of the importance of R&D investments mainly taking place in the universities and in the private sector, which benefit the most to regional innovation activities, having their expenditures and staff employed in R&D activities a positive and statistically significant effects on the innovation process. The findings also show that regions in the Central-North area (North-Western, North-Eastern and Central) outperform the Southern area. Furthermore, the exogenous environmental variables such as labour market and industries' characteristics as well as the proxy for the knowledge context are found to have an important role on RIS efficiency. Statistical significance of both inputs variables and efficiency scores' determinants is not majorly affected by clustering the production function at regional level. The paper is organized as follows. Section 2 introduces the methodology used to estimate RIS efficiency. Section 3 describes the data, the production set and the specification of the models implemented in the analysis. The empirical evidence is described in Section 4, while Section 5 provides a sensitive analysis. Finally Section 6 concludes.

2. Measuring the Regional Innovation System Efficiency

Following Fritsch and Slavtchev (2011), we measure RIS efficiency through the concept of technical efficiency as introduced by Farrell (1957). In other words, a given unit is technically efficient if it is able to produce the possible maximum output from a given amount of input. A KPF [1], based on a Cobb-Douglas production function formulation (see Griliches, 1979 and Jaffe, 1989), is estimated, in order to analyse the relationship between inputs and outputs of the innovation process, which is essential for assessing RIS technical efficiency.

The problem of assessing economic performances of a given unit under analysis (i.e. region), is also exacerbated by inefficiency in production; then, when modeling production and cost functions, it must be kept in mind that a given unit is likely to produce using their inputs in a sub-optimal way. An available approach for incorporating inefficiency into the estimation of production is the method named Stochastic Frontier Analysis (SFA), proposed by Aigner et al. (1977) and Meeusen and Van den Broeck (1977); econometrically, the method assumes that the error term is composed by two components with different distributions (see Kumbhakar and Lovell (2000) for analytical details on stochastic frontier analysis). The first component, regarding the "inefficiency", is asymmetrically distributed (typically as a semi-normal), while the second component, concerning the "error", is distributed as a white noise. In this way, it is necessary to assume that both components are uncorrelated (independent) to avoid distortions in the estimates. This approach is particularly suitable considering our context, as one of the main advantages of SFA is that statistical inference can be drawn, obtaining information on the determinants of inefficiency.

Formally, taking the logarithm version, the KPF is described as follows:

[1] This is based on the assumption that R&D activities are the main source of inventions and innovation.

$$y_{it} = \alpha_i + f(\boldsymbol{x}_{it}, \boldsymbol{\beta})\exp\{v_{it} - u_{it}\} \quad (1)$$

where a is the constant, y_{it} is the output of region i at time t; $\boldsymbol{x}_{it}$ is a vector of input quantities of region i at time t (see Section 3.1 for more details on the input-output framework used in the production set); $\boldsymbol{\beta}$ is a vector of unknown parameters; $f(\boldsymbol{x}_{it}, \boldsymbol{\beta})$ is the production function or conventional regression model; v_{it} is a vector of random variables related to the idiosyncratic or stochastic error term of region i at time t assumed to be independently and identically distributed (i.i.d.) as $N(0, \sigma_v^2)$ and independent of the u_{it}, while u_{it} is a vector of non-negative random variables measuring the inefficiency term of region i at time t assumed to be independently but not identically distributed. They are obtained from the truncation to zero of the distribution $N(m_{it}, \sigma_u^2)$, where $m_{it} = \mu + z_{it}\delta$, μ denoting the location parameter and z_{it} a vector of determinants of (technical) RIS inefficiency of region i at time t (see Section 3.2. for more details on the variables used in z), and δ is a vector of unknown coefficients. In addition, time dummies are also included in the model to capture exogenous factors that might affect the production set and to provide a measure of technological change; time trend and macro-area dummies have also been included in the inefficient component to capture how time and geographical areas determine RIS inefficiency.

All coefficients of parameters in equation (1) and technical efficiency are estimated through a maximum likelihood estimator (MLE) using the STATA 13 software. Following Kalirajan and Shand (1999), we estimate the technical efficiency assuming that output elasticity associated to any input (i.e. $\boldsymbol{\beta}$) is identical for all Italian regions (i=1,.., 20). In other words, the produced output may fall systematically below the maximum, not because of lower output elasticities of the factors of production, but because of a lower level of the function.

3. Data, production set and model specification

3.1 The production set

The empirical analysis is based on data collected from the Italian National Institute of Statistics (ISTAT)[2] covering a 10 years time-span (from 2000 to 2009). The production technology is specified with six inputs (both regarding the R&D expenditures and the number of R&D employees in different sectors) and one output (number of registered patents to the European Patent Office in the years 2000-2009). See Table 1 below for more details on the model specification. More

[2] ISTAT is the Italian National Institute of Statistics (http://www.istat.it/it/), which is a public research organisation been present in Italy since 1926, and is the main producer of official statistics in the service of citizens and policy-makers. It operates in complete independence and continuous interaction with the academic and scientific communities. Data collected are disaggregated at regional territorial level meaning that they are full representative of the 20 regions (corresponding to the NUTS2 type-classification) in Italy. Among the main strengths of ISTAT data is that we can disentangle, for Italian NUTS2 type-classification, the single contribution of HEIs, private and public sector investments in R&D activities – in term of expenditures and number of employees – on the innovative output.

specifically, the first set of inputs consists in the amount of R&D expenditures in the public sector (RD_EXP_PUBL), in the higher education institutions (RD_EXP_HEI) and in the private sector (RD_EXP_PRIV)[3]. See Bottazzi and Peri (2003), Fritsch and Franke (2004), Buesa et al. (2010) and Tavassoli and Carbonara (2014), for the use of similar innovation inputs. The second set of inputs, instead, consists in the number of R&D employees in the public sector (RD_EMPL_PUBL), in the higher education institutions (RD_EMPL_HEI) and in the private sector (RD_EMPL_PRIV).[4] See Fritsch and Slavtchev (2011) and Buesa et al. (2010) for the use of such kind of innovation inputs. As underlined by Buesa et al. (2010), the choice of inputs is based on the conclusion that "innovatory outputs depend in the first place on the effort made in allocating resources, regardless of whether the latter is measured via expenditures or staff employed in R&D". Therefore, the two set of inputs are alternatively used in the knowledge production function in order to explore potential differences due to the way R&D investments are measured in the literature (i.e. R&D expenditures or employees).

[Table 1 around here]

Moving to the output side, we use a standard measure for innovation activities such as the number of patents registered to the European Patent Office in the years 2000-2009 (PAT). Although there are some limitations regarding the use of the number of patents as a measure of innovation output[5], a consistent part of the literature considers them as a good approximation of innovative ideas; indeed, patents are considered to be more objective indicators as an outside patent examiner decides on the suitability of granting a patent to an invention (Mairesse and Mohnen, 2005) and therefore have been recognized as a good approximation of innovative ideas. Among others, Bottazzi and Peri (2003) used the total number of patents granted as a measure of the innovative output of a region; the number of patents invented have been used as a measure of inventive activities by Fernandez-Ribas and Shapira (2009), who investigated the extent to which sector-specific developments in an emerging technology affect inventive activities developed abroad. Buesa et al. (2010), in order to study the determinants of regional innovation in Europe, through a knowledge production function approach, used the number of registered patents as a measure of innovation as well as Fritsch and Slatchev (2011) analysed differences in the efficiency of regional innovation systems using as a measure for innovative output the number of disclosed regional patent applications. Huang and Yu (2011) used the number of applied patents as a measure of firm innovation performances when

[3] The number of R&D expenditures is expressed in thousands of euros. We decide to separate out R&D expenditures in the universities from those in the public sector in order to further analyse the contribution of the higher education institutions to the innovation activities.

[4] The number of R&D employees refers to the researchers, technical employees and any other operator in R&D activities, respectively in the public sector, in the universities and in the private sector. It is expressed as full time equivalent units. We decide to separate out R&D employees in the universities from those in the public sector in order to further analyse the contribution of the higher education institutions to the innovation activities.

[5] First, patents are granted for an invention, but that invention is not necessarily transformed into an innovation, i.e., a new product or production technology. Second, patents are for products rather than for processes. Third, because there are other ways besides patenting to appropriate the returns of successful R&D activities, the number of patents might underestimate actual innovation output (see, among others, Cohen et al. 2000 and Cohen et al. 2002 on this points).

investigating the joint impact of competitive and non-competitive R&D collaborations on firm innovation simultaneously. Wang et al. (2013) examined the moderating effect of specific licensed-knowledge attributes on the innovation performance of licensee firms as measured by the cumulative number of patents applied for as well as Tavassoli and Carbonara (2014) analysed the effect of variety and intensity of knowledge on the innovation of regions as measured by patent applications. Voutsinas et al. (2015), with the aim of underlining the causal relationship between research and development expenditures and innovation, used patents applications as proxy of innovation activity. Vancauteren (2016) analysed the determinants that explain the firm-level output in the Dutch food industry, taking into account patents rather than other innovation outputs as well as D'Ambrosio et al. (2016) investigate the role of search strategy in shaping firms' innovation performance as measured by the number of patents applications. Finally, Subramanian et al. (2016) explored the extent to which diversity of educational levels among research scientists and engineers in the context of a firm's level of technological diversity influences innovation performance as measured by the number of patents applications. More specifically, we follow Fritsch and Slavtchev (2011), assuming that a certain amount of time is required before R&D activities will result in a patent; indeed, several months (usually from 12 to 18) are needed such that patents are published and registered[6]. Therefore, a time lag between innovation inputs and the output of at least one or two years should be assumed[7]. It is true, however, that the time lag between R&D inputs and patent registration also depends on the reliability of the data. Indeed, different solutions have been exploited in the literature; Acs et al. (2002) reported that innovation records result from inventions made 4 years previously, Fritsch and Slavtchev (2007) used a time lag of three years between patent applications and innovation input, Fischer and Varga (2003) used a two-year lag, Ronde and Hussler (2005) estimated regional innovation performances linking the R&D efforts to the number of patents registered one, two and three years later. Fritsch and Slavtchev (2011) reduced the time lag to a period of one year. In order to meet both data constraints and the main literature and also in order to take into account the time required to transform competences into concrete innovation as well as innovation into patents, following Fischer and Varga (2003), we assume a time lag of two years between innovation inputs and outputs.

All inputs and the output variables are in log-levels so that overall the positive skewness of variables is reduced.

When looking at the descriptive statistics (see Tables 2 below for more details), it is interesting to notice that, considering the main four geographical areas of the country, and taking into account the inputs, the Southern area shows the lowest number of both the amount of R&D expenditures and the number of employees in the R&D activities. Moreover, considering the performances in term of R&D outputs (i.e. patents) by geographical areas, again the North-Central areas

[6] This corresponds to the amount of time the patent office needs to verify whether an application fulfills the basic preconditions for being granted a patent and to complete the patent documents (Greif and Schmiedl, 2002).

[7] Assuming such a time lag also helps to avoid potential problems of endogeneity between R&D inputs and outputs.

outperform the Southern area. See Figures 1 and 2 below for a graphical representation of the inputs and the output used in the production function.

[Table 2 around here]

[Figures 1 and 2 around here]

3.2 Determinants of RIS (in)efficiency

In a stochastic frontier model with heterogeneity, failure to model the exogenous factors leads to a biased estimation of the production frontier model and of the level of technical inefficiency, hence leading to poor policy conclusions (e.g. Caudill and Ford 1993; Caudill et al. 1995; Hadri 1999; Wang 2003). Indeed, differences in the economic environment might have an important impact upon RIS inefficiency and various control variables could be used to model this impact. These variables are considered exogenous in the sense that they influence the production process but are not themselves either inputs or outputs. They, in fact, influence the efficiency with which inputs are turned into outputs. Allowing inefficiency to depend on regional environmental characteristics enables researchers to examine the determinants of inefficiency, and to suggest policy interventions to improve efficiency. In other words, the basic assumption of the model is that the environmental factors influence the degree of technical inefficiency and then the innovation production function must include environmental variables which directly influence the inefficiency term. In the specific framework of SFA sometimes a two-stage estimation approach is used, where the first stage involves the specification and estimation of a stochastic frontier and the prediction of the technical efficiency scores of the units and the second one the specification of a regression model where the technical efficiency is regressed on explanatory factors relevant to the analysis; this approach will, however, lead to inconsistent estimates (Kumbhakar and Lovell, 2000); therefore, we apply, instead, a single stage approach (see, for example Battese and Coelli, 1995) where environmental factors are assumed to directly affect technical inefficiency.

In order to adequately measure the effects of some exogenous characteristics on innovation output (i.e. patent), we include in the inefficiency component[8] (see Section 2 for more analytical details) the following explanatory variables: population density (PD); universities' technology transfer offices (TTO); export to GDP (EP_GDP); unemployment rate (UR); employment in services (SERV) and in industry (IND) sectors. More specifically population density (PD), measured as the number of inhabitants in the region by squared kilometres, aims to measure both the effects of urbanization economies and the unobserved region-specific effects. High population density should boost innovation activities as it provides opportunity for intensive contacts and cooperation (for a similar view, see Feldman, 2000 and Fritsch, 2000). Therefore a negative sign

[8] For a similar approach, see Fiordelisi et al. (2011) and Destefanis et al. (2014).

is expected for this variable on RIS inefficiency. Moreover, the technology transfer literature focuses on whether intermediation between businesses and academics helps to reduce the 'cognitive distance' between them, and stimulates knowledge transfer. Therefore, in order to control for the knowledge context in which the firms operate (in terms of research, education and technology transfer-related activities at local universities), the number of the universities' technology transfer offices[9] are used as proxies of academic policies that are oriented towards the commercial exploitation of research results (see Muscio and Nardone, 2012, Maietta, 2015 for the use of such variable). The existence of such intermediation structures controls for the capability of technology transmission[10]. We assume a positive relationship between the presence of TTO's and innovation since company managers and scientists frequently regard TTOs as a facilitator towards successful commercialization of intellectual property rights. A negative sign on innovation inefficiency is then expected to be found on this variable. The unemployment rate (UR), measured as the number of people actively looking for a job as a percentage of the labour force, is intended to capture labour market effects. A positive sign on innovation inefficiency is expected to be found on unemployment. Take into account regional differences in the industry structure is crucial since patenting propensity differs across industries; therefore, in order to control for the impact of regional specialization in certain industries, following Bottazzi and Peri (2003), we use two variables such as the percentages of employment in services (SERV) and in industry (IND) sectors; specifically, SERV and IND are measured, respectively, as the number of employees in services and industry sectors, over the number of total employees in each region. We also use a variable indicating whether the firms are involved in export (EP_GDP) activities; specifically, EP_GDP is measured, as the values of exports as percentage of Gross Domestic Product. A negative sign is expected for these three variables on RIS inefficiency. Finally, time trend control for exogenous effects and macro area dummies capture how geographical areas determine RIS efficiency. See tables 3 and 4 for the definition, the expected sign and the correlation of these variables.

[Tables 3 and 4 around here]

4. Empirical evidence

4.1. *Efficiency scores*

[9] TTOs are offices having the mission of supporting research staff in commercialising the results of scientific research establishing collaborations and mediating between agents. Data from the Italian Network of Technology Transfer Offices of Universities and Public Research Organizations (NETVAL).

[10] Italy represents a very interesting case as, political pressure to commercialise the results of academic research has increased and national laws (D.L. 27/7/1999 no. 297 and D.M. 8/8/2000 no. 593) encourage and regulate the creation of university TTO.

The estimated parameters of a KPF based on Cobb-Douglas specification are presented in Table 5 below. Results are showed when the amount of R&D expenditures are used as inputs (see Table 1 for the specification of the models) and the number of registered patents to the European Patent Office are used as output. In order to take into account that a certain time is required before R&D activities will turn into a patent, a time lag between innovation inputs and the output of two years is assumed. We pay particular attention to both the assumption behind the production function used in the analysis and to inference issues; therefore, we report two estimates for the technical choices and two estimates for the standard errors. Table 5, Columns 1 and 2, reports estimates taking into account the linear homogeneity of degree 1 in inputs, whereas Table 5, Columns 3 and 4, reports estimates relaxing such imposition. Columns 1 and 3 report standard errors robust to heteroscedasticity, whereas Columns 2 and 4 report standard errors clustered at regional and year level. Cluster-adjusted standard errors correct for the possible correlation in innovative performances in the same regions over time. The asymptotic approximation relevant for clustered standard errors relies on a large number of clusters (see Donald and Lang, 2007). We have 200 clusters (10 years* 20 regions) which should be enough to deal with this issue. First of all, the null hypothesis that there is no heteroschedasticity in the error term has been tested and rejected, at 1% significance level, using a Likelihood Ratio Test (LR), giving credit to the use of some exogenous variables, according to which the inefficiency is allowed to change. In other words, the validity of the heteroschedastic assumption has been confirmed, leading to the significance of the inefficiency term. See Figures 3 and 4 for a graphical representation and for boxplots of the RIS efficiency scores.

[Table 5 around here]

[Figures 3 and 4 around here]

The coefficients show that all inputs variables, except for the R&D expenditures in the public sector (RD_EXP_PUBL), have a positive and statistically significant effect on the innovation output, in all the specifications. More specifically, the empirical evidence indicates the existence of significant externalities of private sector and university research activities. In other words, the effect of investing more financial resources in R&D activities on regional innovation performances is higher when more money are devoted to the private sector and to the universities. When looking at the (average) technical efficiency scores by geographical areas (see Table 6 below), the estimates reveal that the Central-North area (North-Western, North-Eastern and Central) outperform the Southern area. Taking for instance estimates in Table 6, Column 1, the highest estimated gap efficiency scores exist between the Southern and the North-Western areas, in the order of 65%. Indeed, the average efficiency of the North-Western area is estimated around 79% - in other words, the output expected can be expanded by almost 20% using the same amount of inputs. Instead, the Southern area is around 15%, thus their inputs can be used more efficiently for producing almost three/fourth more outputs. Estimates are quite similar when the linear homogeneity of degree 1 in inputs has and has not been imposed, but slightly higher in the former case.

[Table 6 around here]

4.2. (In)efficiency score determinants

When considering the exogenous factors included in the analysis, our findings show that the variables used to control for the different environment have an important role in describing the inefficiency term (Table 5). Population density (PD) has a significant and negative effect on RIS inefficiency, indicating that higher level of inhabitants in the region by squared kilometres is associated with higher levels of region's efficiency. This confirms the presence of urbanization economies already found in Fritsch and Slavtchev (2011), where the authors suggest that "densely populated regions provide a variety of opportunities for interaction and rich supplies of inputs, as well as a comprehensive physical and institutional infrastructure is advantageous for innovation activities". The presence of universities' technology transfer offices (TTO) appears to have a positive effect on RIS performances, particularly in the case when the imposition of linear homogeneity of degree 1 in inputs has been relaxed, meaning that the higher is number of universities' technology transfer offices the lower is the inefficiency of innovation activities. In other words, although the introduction of the technology transfer offices was too recent, TTOs carry out the fundamental task of translating business needs into demand for technology, and diffusing the results of scientific research. However, as already specified by Muscio and Nardone (2012), evidence in Italy on the effectiveness of TTOs' management of research contracts with industry and intellectual property rights issues as well as evidence on the real impact of TTOs on knowledge transfer is limited and mostly related to the effects on university–industry relationship (see Muscio, 2010, Siegel et al. 2004, and Piccaluga and Balderi, 2006). Our findings are consistent with the idea that many universities put knowledge transfer high on their agendas and introduce initiatives aimed at linking academic research and industry needs; this is in line with the results by Muscio and Nardone (2012) who find an important role of these offices in building a bridge between academia and industry (in the case of food science departments), being fundamental to technology transfer and, therefore, in attracting private funding. The control for the labour market (UR) seems to have an important role, too. Indeed, a positive and statistically significant coefficient has been found on the unemployment rate variable, meaning that the higher is number of people actively looking for a job as a percentage of the labour force (the higher is the chance of having more workers being involved in innovation activities) the lower is the inefficiency of innovation activities. Regional specialization in certain sectors seem to have relevance on the efficiency of the innovation processes, according to the negative sign of the percentages of employment in industry (IND) sectors. A negative and statistically significant coefficient has been found on the export variable (EP_GDP), meaning that innovation activities, in regions where firms have high values of exports, are more efficient. Finally, according to the negative and significant coefficient (i.e. lower inefficiency) of the dummy variable for location in the North area (NORTH-WESTERN and NORTH-EASTERN)[11], innovation activities in regions located in the western and eastern part of the country are more efficient than those in South, suggesting that there are still considerable differences in the efficiency of the innovative process in the two parts of the country.

5. Sensitivity analysis: Does a different measure of innovation inputs affect the estimates?

In order to take into account the possible evidence of variation in the regional system efficiency and to examine whether an alternative measure of innovative inputs affects the analysis, we use the number of R&D employees (see Fritsch and Slavtchev, 2011, and Buesa et al. 2010 on the use of such inputs) instead of the amount of R&D expenditures (see Table 1 for more details on the production set). More specifically, we again disentangle the contribution to the regional innovative system, by public research institutions, private and public sector. Indeed, the set of inputs consists in the number of R&D employees in the public sector (RD_EMPL_PUBL), in the higher education institutions (RD_EMPL_HEI) and in the private sector (RD_EMPL_PRIV). The innovative output measure still consists in the number of registered patents to the European Patent Office (again, in order to take into account that a certain time is required before R&D activities will turn into a patent, a time lag between innovation inputs and the output of two years is assumed). We report again two estimates for the technical choices and two estimates for the standard errors. Table 7, Columns 1 and 2, reports estimates taking into account the linear homogeneity of degree 1 in inputs, whereas Table 7, Columns 3 and 4, reports estimates relaxing such imposition. Columns 1 and 3, report standard errors robust to heteroscedasticity, whereas Columns 2 and 4, report standard errors clustered at regional and year level. The Likelihood Ratio Test (LR), still confirms the validity of the heteroschedastic assumption, leading to the significance of the inefficiency term.

[Table 7 around here]

Results still show that the coefficients of all inputs variables have a positive and statistically significant effect on the innovation output, in all the specifications, except for the number of R&D employees in the public sector (RD_EMPL_PUBL). This means that when the R&D employees are used as innovative input, again the empirical findings suggest the importance of R&D investments taking place in the universities and in the private sector, which benefit the most

[11] The use of such variables allows us to control for potential geographical differences and therefore for the heterogeneity within the country.

to regional innovation activities. When looking at the (average) technical efficiency scores by geographical areas (see Table 8 below), the estimates confirm the presence of some geographical effects (by macro-areas) with Central-North regions (North-Western, North-Eastern and Central) outperforming those in the Southern area. When considering the exogenous factors included in the analysis, the findings confirm that the variables used to control for the different environment have an important role in describing the inefficiency term (Table 7). Population density (PD), the control for the labour market (UR) and the export variable (EP_GDP) confirm the statistical significance and the sign expected. Regional specialization in certain sectors (IND variable) also seems to have relevance on the efficiency of the innovation processes (see Table 7, Columns 3 and 4). When the linear homogeneity of degree 1 in inputs has not been assumed, results confirmed also the importance of capability of technology transmission proxied by the existence of an intermediation structure, such as a universities' technology transfer offices (TTO).

[Table 8 around here]

6. Summary and conclusions

In this paper, we investigate the regional innovation system efficiency in the Italian context, by estimating a measure of efficiency based on the knowledge production function concept. More specifically, a Stochastic Frontier Analysis, in order to analyse the relationship between inputs and outputs of the innovation process, has been applied. This parametric approach is particularly suitable considering the context analysed, as one of its advantage is that statistical inference can be drawn; indeed, obtaining information on the determinants of inefficiency and consequently on the estimated parameters, may attract the interest of regulators and decision makers towards the adoption of improving policies regarding the production of knowledge within a region leading to innovation activities and patents registered. Our contribution to the expanding literature on innovation performances is to investigate the extent to which sector-specific development, such as increasing expenditures and staff employed in R&D activities, affect inventive activities at regional level. The contribution of private and public sector resources devoted to research and development, in generating innovation, has been considered, as well as the impact of several exogenous environmental variables. Taking into account the measures of inputs in the innovative process, we disentangled the contribution (both considering the amount of R&D expenditures and the number of R&D employees) to the regional innovative system output (number of registered patents to the European Patent Office) by higher education institutions, private and public sector. Several exogenous variables such as labour market and industries' characteristics as well as a proxy for knowledge context are used in order to examine whether the economic environment has an impact upon RIS inefficiency.

Among the theoretical determinant of innovation performances there are both expenditures and employees in R&D

activities. The empirical evidence shows that the coefficients of such input variables, almost in all specifications, have a positive and statistically significant effect on the regional innovation system efficiency; more specifically, the empirical evidence suggests that it is particularly the contribution of higher education institutions' and private firms' research activities to increase regional innovation efficiency. Indeed, the relationship between their R&D resources and innovative performances is positive and significant meaning that the money and human capital allocated on R&D by university and private sector does have effects on patents more that in the public sector. Probably the government laboratories have not attracted and generated as much attention as universities and the institutions operating in the private sector. Moreover, do not appear significant differences in the contribution of R&D expenditures and human capital employed in R&D activities, confirming the idea that it is the allocation more than the choice of inputs to be effective on innovative outputs (Buesa et al. 2010). Findings also show that regions in the Central-North area (North-Western, North-Eastern and Central) outperform the Southern area with the highest estimated gap efficiency scores existing between the Southern area and the North-Western area. A number of factors were found having a positive impact on RIS efficiency. Population density has a positive effect on innovation performances meaning that R&D activities are more productive in area more urbanized; RIS performances are found to be also influenced by the labour market and firm characteristics; indeed, innovation performances seem to be positively influenced by the rate of employment and by the presence of firms with high values of exports; RIS performance is positively affected by the share of employees in industry sectors; the evidence also suggest the relevance of the knowledge context in which the firms operate as the existence of an intermediation structure, such as universities' technology transfer offices, has an important role on the innovation process.

The empirical evidence provided calls into question possible limitations, some important policy implications as well as important issues to be further analysed in some future research. Indeed, a potential concern of our analysis regards the limited sample and the possibility of drawing robust conclusions with a max 200 observations. It has to be said, however, that although focusing on regional data in one country may bring to life some problems regarding the number of observations, it also reduces the heterogeneity, counting on a higher level of cultural, political and economic homogeneity country-wise. It could have been optimal to use more disaggregated data, such as at province level (corresponding to the NUTS3 type-classification); unfortunately, we cannot investigate the innovation system at such territorial level due to the lack of information (more specifically, ISTAT data do not allow us to disentangle, for provinces or municipalities, the single contribution of HEIs, private and public sectors' investments in R&D activities – in term of expenditures and number of employees – on the innovative output). Keeping this discussion in mind, we believe that some lessons can be learned from this analysis. Firstly, the gap in efficiency among the macro-areas of the country requires some explanation, which can be useful for defining consistent policies that can improve the innovation productivity of the overall system; we claim that maintaining State-level policies can be detrimental for overall efficiency, and instead special interventions for regions in the South should be designed. A further consideration relates to the large investment that regional governments and academic institutions need to make to create TTOs. Indeed, they contribute significantly to knowledge transfer and, by filling a gap between academic research and industry needs and by strengthening the governance and management of university–industry interactions, stimulate the innovation process. This calls for a greater specialization of TTOs, an increase in their number of staff and in their employees’ technology backgrounds. Finally, a policy that aims at improving RIS efficiency should be able to identify the most efficient channels through which knowledge transfer and innovation activities could be stimulated. The findings provide a clue towards the expansion of the importance of R&D investments taking place in the universities and in the private sector, which benefit the most to regional innovation activities. Further research is needed, using more disaggregated data, in order to disentangle the policy implications at province level.

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Tables and Figures

Table n. 1 - Specification of inputs, outputs and exogenous factors in SFA models

	Model A	Model B
Inputs	*RD_EXP_PUBL; RD_EXP_HEI; RD_EXP_PRIV*	*RD_EMP_PUBL; RD_EMP_HEI; RD_EMP_PRIV*
Outputs	*PAT*	*PAT*
Explaining the inefficiency E(U)	*PD; TTO; EP_GDP; UR; SERV; IND*	*PD; TTO; EP_GDP; UR; SERV; IND*

Notes:
RD_EXP_PUBL: R&D expenditures in the public sector
RD_EXP_HEI: R&D expenditures in higher education institutions
RD_EXP_PRIV: R&D expenditures in the private sector
RD_EMP_PUBL: Number of R&D employees in the public sector
RD_EMP_HEI: Number of R&D employees in higher education institutions
RD_EMP_PRIV: Number of R&D employees in the private sector
PAT: Number of registered regional patents to the European Patent Office
PD: Population density
TTO: Universities' technology transfer offices
EP_GDP: Values of exports as percentage of Gross Domestic Product
UR: Unemployment rate
SERV: Employment in the services sector
IND: Employment in the industry sector

Table 2 – Descriptive statistics by macro areas

Variables	***North-Western***	***North-Eastern***	***Central***	***Southern***	***Total***
Production function parameters					
PAT (in log)	*514.282*	*378.06*	*159.045*	*35.411*	*225.392*
RD_EXP_PUBL	*100365.2*	*95556.74*	*354830.1*	*48409.69*	*129514.3*
RD_EXP_HEI	*275722.9*	*249508.8*	*344440.3*	*193837.9*	*251469.5*
RD_EXP_PRIV	*1050356*	*427988.8*	*326553.1*	*99558.35*	*400802.8*
RD_EMP_PUBL	*1357.71*	*1185.305*	*4332.097*	*701.387*	*1655.57*
RD_EMP_HEI	*3574.368*	*3249.103*	*4446.323*	*2636.945*	*3308.737*
RD_EMP_PRIV	*9655.287*	*5101.49*	*3105.952*	*1018.036*	*3979.76*
Explaining the inefficiency - E(U)					
PD	*221.413*	*166.18*	*178.976*	*159.142*	*176.971*
TTO	*3*	*2.25*	*3*	*1.375*	*2.2*
EP_GDP	*31.425*	*22.630*	*29.135*	*33.945*	*30.216*
UR	*5.397*	*3.727*	*6.082*	*13.068*	*8.269*
SERV	*0.6755*	*0.6162*	*0.6643*	*0.6699*	*0.6592*
IND	*0.2950*	*0.3394*	*0.3032*	*0.2548*	*0.2894*

Notes: Patents (PAT) represent the output. The first set of inputs consists in the amount of R&D expenditures in the public sector (RD_EXP_PUBL), in the higher education institutions (RD_EXP_HEI) and in the private sector (RD_EXP_PRIV). The second set of inputs, instead, consists in the number of R&D employees in the public sector (RD_EMPL_PUBL), in the higher education institutions (RD_EMPL_HEI) and in the private sector (RD_EMPL_PRIV). PD: Population density (measured as the number inhabitants in the region by squared kilometer); TTO: Technology transfer office (measured as the number of university technology transfer offices); EP_GDP: export (measured as the values of exports as a percentage of the Gross Domestic Product); UR: Unemployment rate (measured as the number of people actively looking for a job as a percentage of the labour force); SERV: employment in the services sector (measured as the number of employees in the services sector over the total number of employees); IND: employment in the industry sector (measured as the number of employees in the industry sector over the total number of employees). All monetary aggregates are in thousands of deflated 2005 Euros.

Table 3 – Definition of the variables and expected sign

Symbol	***Description***	***Expected sign***
Production function parameter		
RD_EXP_PUBL	*R&D expenditures in the public sector*	+
RD_EXP_HEI	*R&D expenditures in higher education institutions*	+
RD_EXP_PRIV	*R&D expenditures in the private sector*	+
RD_EMP_PUBL	*Number of R&D employees in the public sector*	+
RD_EMP_HEI	*Number of R&D employees in higher education institutions*	+
RD_EMP_PRIV	*Number of R&D employees in the private sector*	+
Explaining the inefficiency - E(U)		
PD	*Population density*	-
TTO	*University technology transfer office*	-
EP_GDP	*Values of exports as percentage of Gross Domestic Product*	-
UR	*Unemployment rate*	+
SERV	*Employment in the services sector*	-
IND	*Employment in the industry sector*	-

Notes: The first set of inputs consists in the amount of R&D expenditures in the public sector (RD_EXP_PUBL), in the higher education institutions (RD_EXP_HEI) and in the private sector (RD_EXP_PRIV). The second set of inputs, instead, consists in the number of R&D employees in the public sector (RD_EMPL_PUBL), in the higher education institutions (RD_EMPL_HEI) and in the private sector (RD_EMPL_PRIV). PD: Population density (measured as the number inhabitants in the region by squared kilometer); TTO: Technology transfer office (measured as the number of university technology transfer offices); EP_GDP: export (measured as the values of exports as a percentage of the Gross Domestic Product); UR: Unemployment rate (measured as the number of people actively looking for a job as a percentage of the labour force); SERV: employment in the services sector (measured as the number of employees in the services sector over the total number of employees); IND: employment in the industry sector (measured as the number of employees in the industry sector over the total number of employees).

Table 4 – Correlation between variables

		1	***2***	***3***	***4***	***5***	***6***	***7***	***8***	***9***	***10***	***11***	***12***	***13***	***14***
1	*RIS*	*1.000*													
2	*PAT*	*0.684****	*1.000*												
3	*RD_EXP_PUBL*	*-0.099*	*0.167***	*1.000*											
4	*RD_EXP_HEI*	*0.161***	*0.634****	*0.573****	*1.000*										
5	*RD_EXP_PRIV*	*0.573****	*0.915****	*0.311****	*0.690****	*1.000*									
6	*RD_EMPL_PUBL*	*-0.099*	*0.178****	*0.989****	*0.600****	*0.333****	*1.0000*								
7	*RD_EMPL_HEI*	*0.141**	*0.631****	*0.570****	*0.975****	*0.689****	*0.598****	*1.000*							
8	*RD_EMPL_PRIV*	*0.616****	*0.924****	*0.270****	*0.679****	*0.985****	*0.290****	*0.684****	*1.000*						
9	*PD*	*0.103*	*0.520****	*0.425****	*0.760****	*0.578****	*0.443****	*0.764****	*0.566****	*1.000*					
10	*TTO*	*0.357****	*0.7570****	*0.573****	*0.751****	*0.787****	*0.582****	*0.758****	*0.762****	*0.590****	*1.000*				
11	*EP_GDP*	*-0.253****	*0.029*	*0.512****	*0.214****	*0.204****	*0.511****	*0.217****	*0.160***	*0.288****	*0.205****	*1.000*			
12	*UR*	*-0.801****	*-0.447****	*-0.045*	*-0.057*	*-0.347****	*-0.041*	*-0.028*	*-0.376****	*0.049*	*-0.227****	*0.206****	*1.000*		
13	*SERV*	*0.303****	*0.809****	*0.505****	*0.917****	*0.845****	*0.526****	*0.915****	*-0.830****	*0.805****	*0.8691****	*0.222****	*-0.086*	*1.000*	
14	*IND*	*0.562****	*0.918****	*0.214****	*0.728****	*0.857****	*0.230****	*0.730****	*0.873****	*0.628****	*0.751****	*0.048*	*-0.304****	*0.864****	*1.000*

Notes: Regional Innovation System (RIS) efficiency denotes the technical efficiency calculated using a knowledge production function (KPF). Patents (PAT) represent the output. The set of inputs consists in the amount of R&D expenditures in the public sector (RD_EXP_PUBL), in the higher education institutions (RD_EXP_HEI) and in the private sector (RD_EXP_PRIV). PD: Population density (measured as the number inhabitants in the region by squared kilometer); TTO: Technology transfer office (measured as the number of university technology transfer offices); EP_GDP: export (measured as the values of exports as a percentage of the Gross Domestic Product); UR: Unemployment rate (measured as the number of people actively looking for a job as a percentage of the labour force); SERV: employment in the services sector (measured as the number of employees in the services sector over the total number of employees); IND: employment in the industry sector (measured as the number of employees in the industry sector over the total number of employees).

Table 5 - Estimates for the knowledge production function and for the inefficiency components according to the stochastic frontier approach - Mean values

Variables	***Model A***			
	(1)	***(2)***	***(3)***	***(4)***
Production function parameters				
RD_EXP_PUBL (in log)	*0.052*	*0.052*	*0.121*	*0.121*
	(0.086)	*(0.156)*	*(0.081)*	*(0.183)*
RD_EXP_HEI (in log)	*0.675****	*0.675****	*0.573****	*0.573****
	(0.060)	*(0.081)*	*(0.057)*	*(0.064)*
RD_EXP_PRIV (in log)	*0.271****	*0.271*	*0.143****	*0.143*
	(0.080)	*(0.181)*	*(0.047)*	*(0.106)*
Explaining the inefficiency				
PD (in log)	*-0.353****	*-0.353***	*-0.487****	*-0.487****
	(0.076)	*(0.137)*	*(0.071)*	*(0.134)*
TTO	*-0.068*	*-0.068*	*-0.092***	*-0.092****
	(0.042)	*(0.041)*	*(0.038)*	*(0.033)*
EP_GDP (in log)	*-0.347****	*-0.347****	*-0.349****	*-0.349****
	(0.083)	*(0.108)*	*(0.082)*	*(0.126)*
UR (in log)	*1.055****	*1.055***	*0.918****	*0.918****
	(0.243)	*(0.412)*	*(0.185)*	*(0.203)*
SERV (%)	*0.374*	*0.374*	*-3.011*	*-3.011*
	(2.504)	*(2.411)*	*(2.366)*	*(1.893)*
IND (%)	*-1.448*	*-1.448*	*-6.755****	*-6.755****
	(3.174)	*(5.413)*	*(2.226)*	*(2.331)*
NORTH-WESTERN	*-1.271****	*-1.271*	*-1.646****	*-1.646****
	(0.395)	*(0.841)*	*(0.279)*	*(0.622)*
NORTH-EASTERN	*-0.872****	*-0.872****	*-0.930****	*-0.930****
	(0.278)	*(0.341)*	*(0.254)*	*(0.284)*
CENTRAL	*-0.212*	*-0.212*	*-0.203*	*-0.203*
	(0.186)	*(0.201)*	*(0.177)*	*(0.211)*
Log-likelihood	*-53.9530*	*-53.9530*	*-30.2805*	*-30.2805*
LR test for null inefficiency component ($p > \chi^2$)	*179.96*	-	*221.47*	-
	(0.0000)		*(0.0000)*	
Wald statistic	*66.94*	*254.94*	*543.47*	*1319.80*
σ_u	*0.255****	*0.255*	*0.346****	*0.346****
	(0.065)	*(0.176)*	*(0.030)*	*(0.086)*
σ_v	*0.263****	*0.263****	*0.102****	*0.102**
	(0.040)	*(0.101)*	*(0.029)*	*(0.057)*
λ	*0.969****	*0.969****	*3.390****	*3.390****
	(0.100)	*(0.262)*	*(0.052)*	*(0.133)*
N	*160*	*160*	*160*	*160*
Time dummies in the frontier	*Yes*	*Yes*	*Yes*	*Yes*
Time trend in E(U)	*Yes*	*Yes*	*Yes*	*Yes*

Notes: Model A, Column 1, with the imposition of the linear homogeneity of degree 1 in inputs; Model A, Column 2, with the imposition of the linear homogeneity of degree 1 in inputs and standard errors clustered at region and year level; Model A, Column 3, without the imposition of the linear homogeneity of degree 1 in inputs; Model A, Column 4, without the imposition of the linear homogeneity of degree 1 in inputs and standard errors clustered at region and year level. The set of inputs consists in the amount of R&D expenditures in the public sector (RD_EXP_PUBL), in the higher education institutions (RD_EXP_HEI) and in the private sector (RD_EXP_PRIV). PD: Population density (measured as the number inhabitants in the region by squared kilometer); TTO: Technology transfer office (measured as the number of university technology transfer offices); EP_GDP: export (measured as the values of exports as a percentage of the Gross Domestic Product); UR: Unemployment rate (measured as the number of people actively looking for a job as a percentage of the labour force); SERV: employment in the services sector (measured as the number of employees in the services sector over the total number of employees); IND: employment in the industry sector (measured as the number of employees in the industry sector over the total number of employees). All models consider time dummies in the frontier and in the inefficiency component. Southern area is our benchmark group. Standard errors in brackets. The LR test evaluates the restricted and unrestricted models with and without the exogenous factors in the inefficiency term (the null hypothesis that there is no heteroschedasticity in the error term is rejected, at 1% significance level in all the models).

Table 6 – Technical efficiency by macro areas and by regions according to the stochastic frontier approach

	Model A							
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
	Mean	***Std. Dev.***	***Min***	***Max***	***Mean***	***Std. Dev.***	***Min***	***Max***
Geographical areas								
Central	*0.3791*	*0.1779*	*0.1546*	*0.7869*	*0.3030*	*0.1510*	*0.1278*	*0.6294*
Nord-Eastern	*0.7880*	*0.1344*	*0.4959*	*0.9464*	*0.6633*	*0.2286*	*0.3405*	*0.9545*
North-Western	*0.7924*	*0.2196*	*0.3207*	*0.9624*	*0.7000*	*0.2724*	*0.2279*	*0.9719*
Southern	*0.1515*	*0.0553*	*0.0499*	*0.3302*	*0.1060*	*0.0506*	*0.0110*	*0.2505*
Regions								
Abruzzo	*0.2677*	*0.0358*	*0.2258*	*0.3302*	*0.2075*	*0.0270*	*0.1812*	*0.2505*
Basilicata	*0.1407*	*0.0276*	*0.0947*	*0.1718*	*0.0774*	*0.0293*	*0.0317*	*0.1052*
Calabria	*0.1625*	*0.0226*	*0.1319*	*0.1879*	*0.0937*	*0.0227*	*0.0630*	*0.1209*
Campania	*0.1167*	*0.0178*	*0.0886*	*0.1413*	*0.1029*	*0.0203*	*0.0633*	*0.1283*
Emilia.Romagna	*0.8967*	*0.0454*	*0.7946*	*0.9464*	*0.8559*	*0.0748*	*0.6854*	*0.9228*
Friuli.Venezia Giulia	*0.5959*	*0.0661*	*0.4959*	*0.6881*	*0.4476*	*0.0725*	*0.3405*	*0.5429*
Lazio	*0.1867*	*0.0165*	*0.1546*	*0.2132*	*0.1557*	*0.0130*	*0.1278*	*0.1718*
Liguria	*0.4520*	*0.0914*	*0.3207*	*0.6002*	*0.3200*	*0.0702*	*0.2279*	*0.4033*
Lombardia	*0.9548*	*0.0080*	*0.9383*	*0.9624*	*0.9640*	*0.0091*	*0.9445*	*0.9719*
Marche	*0.6301*	*0.1043*	*0.4886*	*0.7869*	*0.5043*	*0.1095*	*0.3728*	*0.6294*
Molise	*0.1003*	*0.0373*	*0.0499*	*0.1467*	*0.0435*	*0.0289*	*0.0110*	*0.0909*
Piemonte	*0.9127*	*0.0352*	*0.8266*	*0.9317*	*0.8554*	*0.0793*	*0.6619*	*0.9093*
Puglia	*0.1630*	*0.0241*	*0.1231*	*0.1932*	*0.1263*	*0.0241*	*0.0825*	*0.1554*
Sardegna	*0.1232*	*0.0307*	*0.0890*	*0.1859*	*0.0774*	*0.0232*	*0.0434*	*0.1119*
Sicilia	*0.1253*	*0.0100*	*0.1110*	*0.1439*	*0.1030*	*0.0218*	*0.0718*	*0.1329*
Toscana	*0.4081*	*0.0470*	*0.3494*	*0.4732*	*0.3523*	*0.0294*	*0.3195*	*0.3891*
Trentino Alto Adige	*0.7623*	*0.0491*	*0.7000*	*0.8356*	*0.4471*	*0.0691*	*0.3445*	*0.5195*
Umbria	*0.2917*	*0.0540*	*0.2235*	*0.3777*	*0.1998*	*0.0433*	*0.1371*	*0.2603*
Valle d'Aosta	*0.8693*	*0.0920*	*0.7126*	*0.9327*	*0.6474*	*0.1739*	*0.3446*	*0.8586*
Veneto	*0.8973*	*0.0336*	*0.8197*	*0.9282*	*0.9026*	*0.0379*	*0.8309*	*0.9545*

Notes: Model A, Columns 1, 2, 3 and 4, with the imposition of the linear homogeneity of degree 1 in inputs; Model A, Columns 5, 6, 7 and 8, without the imposition of the linear homogeneity of degree 1 in inputs.

Table 7 - Estimates for the knowledge production function and for the inefficiency components according to the stochastic frontier approach - Mean values

Variables	*Model B*			
	(1)	*(2)*	*(3)*	*(4)*
Production function parameters				
RD_EMPL_PUBL (in log)	*0.233***	*0.233*	*0.105*	*0.105*
	(0.103)	*(0.328)*	*(0.077)*	*(0.107)*
RD_EMPL_HEI (in log)	*0.518****	*0.518**	*0.585****	*0.585****
	(0.087)	*(0.314)*	*(0.057)*	*(0.059)*
RD_EMPL_PRIV (in log)	*0.248****	*0.248***	*0.160****	*0.160***
	(0.056)	*(0.105)*	*(0.047)*	*(0.070)*
Explaining the inefficiency				
PD (in log)	*-0.495****	*-0.495***	*-0.521****	*-0.521****
	(0.083)	*(0.194)*	*(0.068)*	*(0.109)*
TTO	*-0.039*	*-0.039*	*-0.079***	*-0.079****
	(0.041)	*(0.047)*	*(0.037)*	*(0.026)*
EP_GDP (in log)	*-0.441****	*-0.441***	*-0.356****	*-0.356****
	(0.094)	*(0.218)*	*(0.077)*	*(0.095)*
UR (in log)	*0.979****	*0.979****	*0.999****	*0.999****
	(0.226)	*(0.363)*	*(0.183)*	*(0.198)*
SERV (%)	*-1.757*	*-1.757*	*-4.241**	*-4.241***
	(2.493)	*(2.288)*	*(2.300)*	*(1.994)*
IND (%)	*-4.691**	*-4.691*	*-7.034****	*-7.034****
	(2.818)	*(4.389)*	*(2.292)*	*(2.122)*
NORTH-WESTERN	*-1.568****	*-1.568***	*-1.624****	*-1.624****
	(0.324)	*(0.690)*	*(0.254)*	*(0.476)*
NORTH-EASTERN	*-0.993****	*-0.993***	*-0.943****	*-0.943****
	(0.289)	*(0.421)*	*(0.247)*	*(0.309)*
CENTRAL	*-0.272*	*-0.272*	*-0.172*	*-0.172*
	(0.199)	*(0.342)*	*(0.174)*	*(0.227)*
Log-likelihood	*-45.4981*	*-45.4981*	*-26.6493*	*-26.6493*
LR test for null inefficiency component ($p > \chi^2$)	*198.69*	*-*	*235.49*	*-*
	(0.0000)		*(0.0000)*	
Wald statistic	*42.85*	*178.21*	*1004.27*	*9947.73*
σ_u	*0.343****	*0.343***	*0.342****	*0.342****
	(0.046)	*(0.155)*	*(0.025)*	*(0.066)*
σ_v	*0.163****	*0.163*	*0.090****	*0.090***
	(0.044)	*(0.119)*	*(0.024)*	*(0.035)*
λ	*2.094****	*2.094*	*3.802****	*3.802****
	(0.086)	*(0.267)****	*(0.042)*	*(0.089)*
N	*156*	*156*	*156*	*156*
Time dummies in the frontier	*160*	*160*	*160*	*160*
Time trend in E(U)	*Yes*	*Yes*	*Yes*	*Yes*

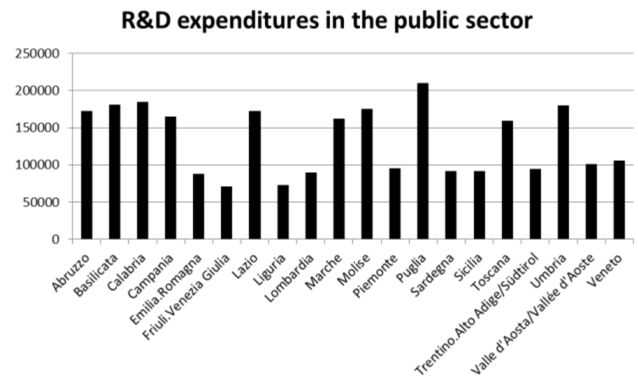
Notes: Model B, Column 1, with the imposition of the linear homogeneity of degree 1 in inputs; Model B, Column 2, with the imposition of the linear homogeneity of degree 1 in inputs and standard errors clustered at region and year level; Model B, Column 3, without the imposition of the linear homogeneity of degree 1 in inputs; Model B, Column 4, without the imposition of the linear homogeneity of degree 1 in inputs and standard errors clustered at region and year level. The set of inputs consists in the number of R&D employees in the public sector (RD_EMPL_PUBL), in the higher education institutions (RD_EMPL_HEI) and in the private sector (RD_EMPL_PRIV). PD: Population density (measured as the number inhabitants in the region by squared kilometer); TTO: Technology transfer office (measured as the number of university technology transfer offices); EP_GDP: export (measured as the values of exports as a percentage of the Gross Domestic Product); UR: Unemployment rate (measured as the number of people actively looking for a job as a percentage of the labour force); SERV: employment in the services sector (measured as the number of employees in the services sector over the total number of employees); IND: employment in the industry sector (measured as the number of employees in the industry sector over the total number of employees). All models consider time dummies in the frontier and in the inefficiency component. Southern area is our benchmark group. Standard errors in brackets. The LR test evaluates the restricted and unrestricted models with and without the exogenous factors in the inefficiency term (the null hypothesis that there is no heteroschedasticity in the error term is rejected, at 1% significance level in all the models).

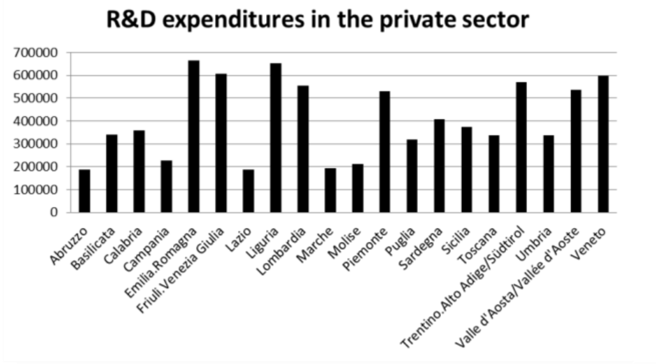
Table 8 – Technical efficiency by macro areas and by regions according to the stochastic frontier approach

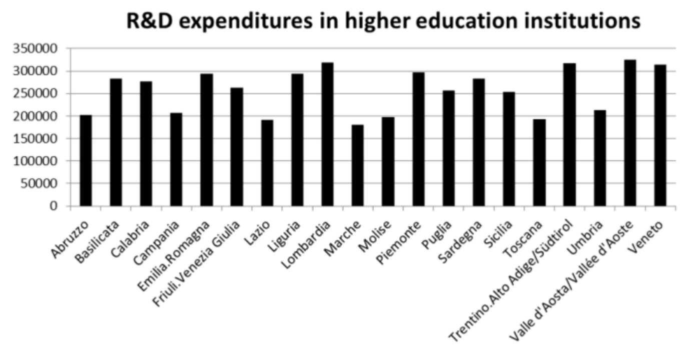
	Model B							
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
	Mean	***Std. Dev.***	***Min***	***Max***	***Mean***	***Std. Dev.***	***Min***	***Max***
Geographical areas								
Central	*0.3514*	*0.1910*	*0.1111*	*0.8001*	*0.2818*	*0.1284*	*0.1150*	*0.5517*
Nord-Eastern	*0.7130*	*0.1765*	*0.3683*	*0.9375*	*0.6555*	*0.2185*	*0.2950*	*0.9529*
North-Western	*0.7561*	*0.2480*	*0.2719*	*0.9535*	*0.6967*	*0.2771*	*0.2348*	*0.9738*
Southern	*0.1357*	*0.0592*	*0.0232*	*0.3053*	*0.0993*	*0.0490*	*0.0096*	*0.2423*
Regions								
Abruzzo	*0.2529*	*0.0312*	*0.1957*	*0.3053*	*0.1982*	*0.0238*	*0.1605*	*0.2423*
Basilicata	*0.1029*	*0.0306*	*0.0449*	*0.1341*	*0.0657*	*0.0219*	*0.0239*	*0.0886*
Calabria	*0.1577*	*0.0383*	*0.1088*	*0.2345*	*0.0923*	*0.0231*	*0.0621*	*0.1307*
Campania	*0.1105*	*0.0246*	*0.0729*	*0.1529*	*0.0991*	*0.0240*	*0.0610*	*0.1407*
Emilia.Romagna	*0.8396*	*0.0851*	*0.6421*	*0.9132*	*0.8218*	*0.0895*	*0.6327*	*0.9240*
Friuli.Venezia Giulia	*0.5601*	*0.0734*	*0.4249*	*0.6552*	*0.4507*	*0.0660*	*0.3313*	*0.5371*
Lazio	*0.1318*	*0.0159*	*0.1111*	*0.1623*	*0.1599*	*0.0191*	*0.1315*	*0.1973*
Liguria	*0.3833*	*0.0828*	*0.2719*	*0.4910*	*0.3356*	*0.0685*	*0.2348*	*0.4241*
Lombardia	*0.9392*	*0.0112*	*0.9197*	*0.9491*	*0.9646*	*0.0105*	*0.9457*	*0.9738*
Marche	*0.6075*	*0.1187*	*0.4408*	*0.8001*	*0.4270*	*0.0774*	*0.3320*	*0.5517*
Molise	*0.0802*	*0.0550*	*0.0232*	*0.1739*	*0.0389*	*0.0284*	*0.0096*	*0.0879*
Piemonte	*0.8867*	*0.0636*	*0.7304*	*0.9197*	*0.8619*	*0.0986*	*0.6223*	*0.9245*
Puglia	*0.1429*	*0.0241*	*0.1114*	*0.1791*	*0.1144*	*0.0187*	*0.0916*	*0.1396*
Sardegna	*0.1005*	*0.0253*	*0.0621*	*0.1344*	*0.0691*	*0.0182*	*0.0396*	*0.0962*
Sicilia	*0.1242*	*0.0263*	*0.0874*	*0.1677*	*0.1013*	*0.0240*	*0.0668*	*0.1003*
Toscana	*0.4027*	*0.0476*	*0.3537*	*0.4716*	*0.3696*	*0.0384*	*0.3327*	*0.4313*
Trentino Alto Adige	*0.5538*	*0.0993*	*0.3683*	*0.6532*	*0.4586*	*0.0889*	*0.2950*	*0.5537*
Umbria	*0.2636*	*0.0565*	*0.1815*	*0.3732*	*0.1706*	*0.0353*	*0.1150*	*0.2325*
Valle d'Aosta	*0.8352*	*0.1750*	*0.4824*	*0.9535*	*0.6005*	*0.2165*	*0.2567*	*0.8824*
Veneto	*0.8986*	*0.0465*	*0.7889*	*0.9375*	*0.8910*	*0.0635*	*0.7454*	*0.9529*

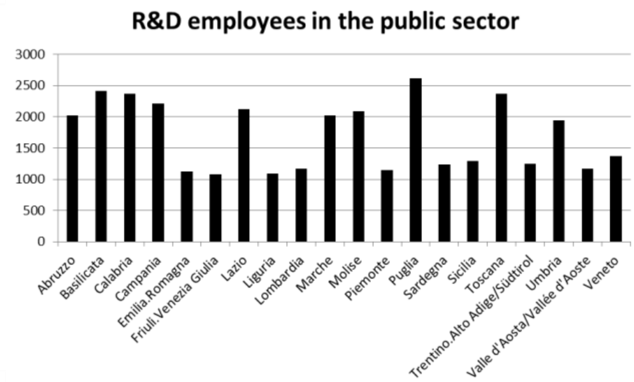
Notes: Model B, Columns 1, 2, 3 and 4, with the imposition of the linear homogeneity of degree 1 in inputs; Model B, Columns 5, 6, 7 and 8, without the imposition of the linear homogeneity of degree 1 in inputs.

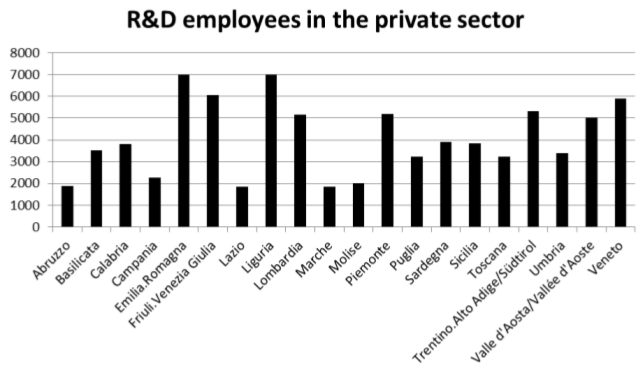
Figure 1 – Inputs and outputs used in the production function over 2000–2009 time-span, by regions

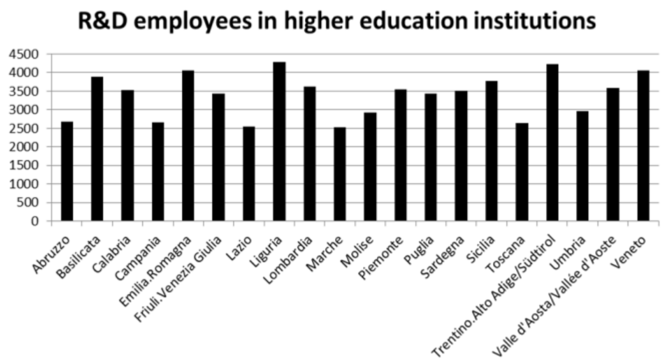












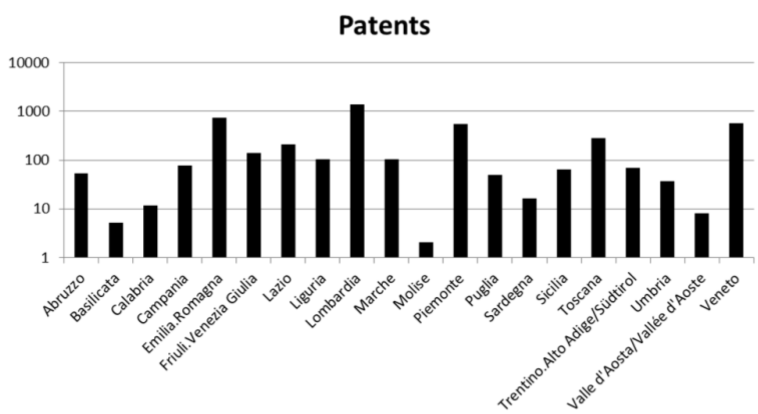


Figure 2 – Inputs used in the production function, by sectors, by regions and by tertiles

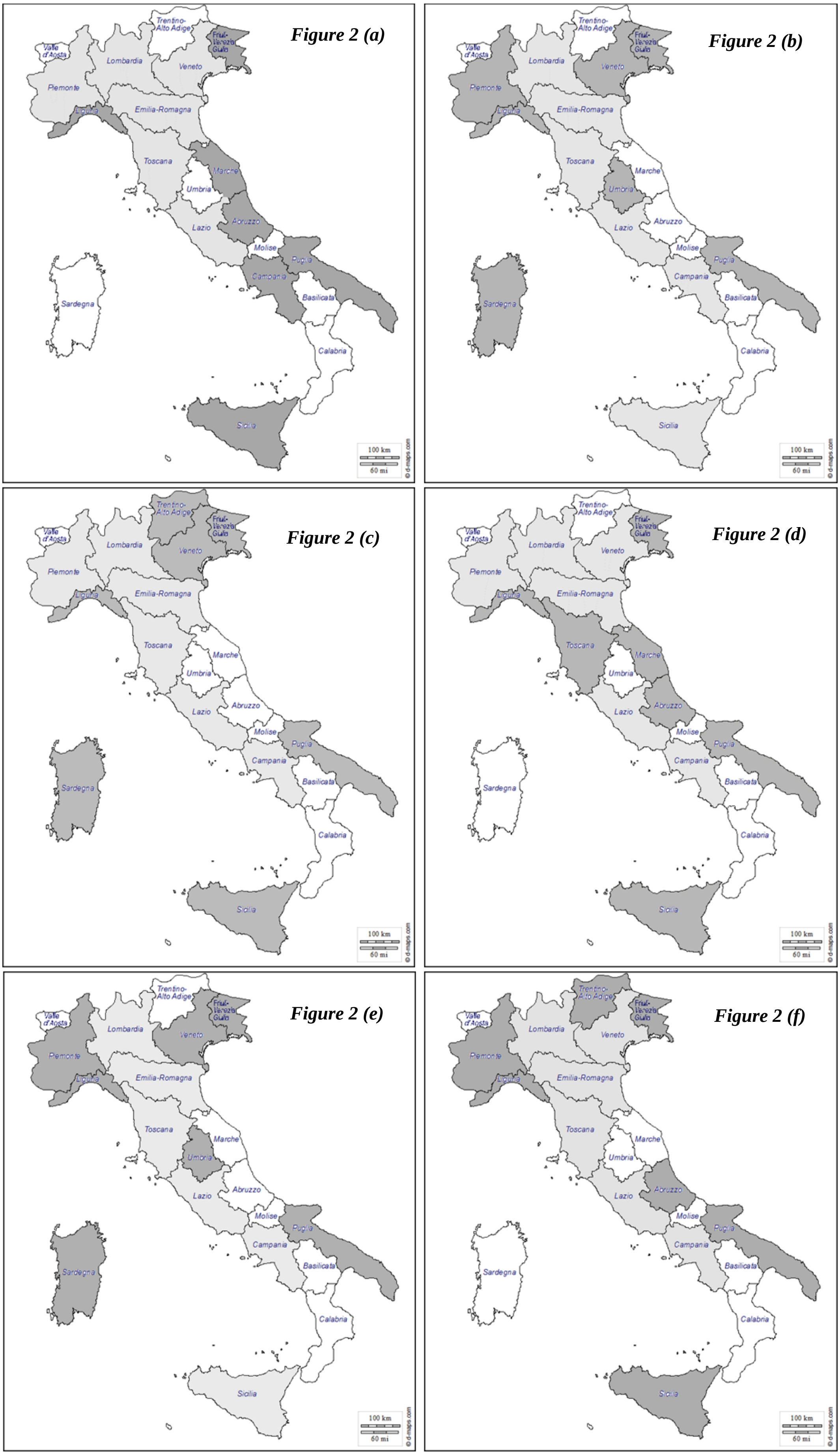


Figure 2(a)-2(b)-2(c) shows the number of R&D expenditures, respectively, in private sector, higher education institutions and public sector.
Figure 2(d)-2(e)-2(f) shows the number of R&D employees, respectively, in private sector, higher education institutions and public sector.
In white, regions within the first tertile; in dark grey, regions within the second tertile; in light grey, regions within the third quartile.

Figure 3 – Patents and RIS efficiency scores - by regions and by tertiles

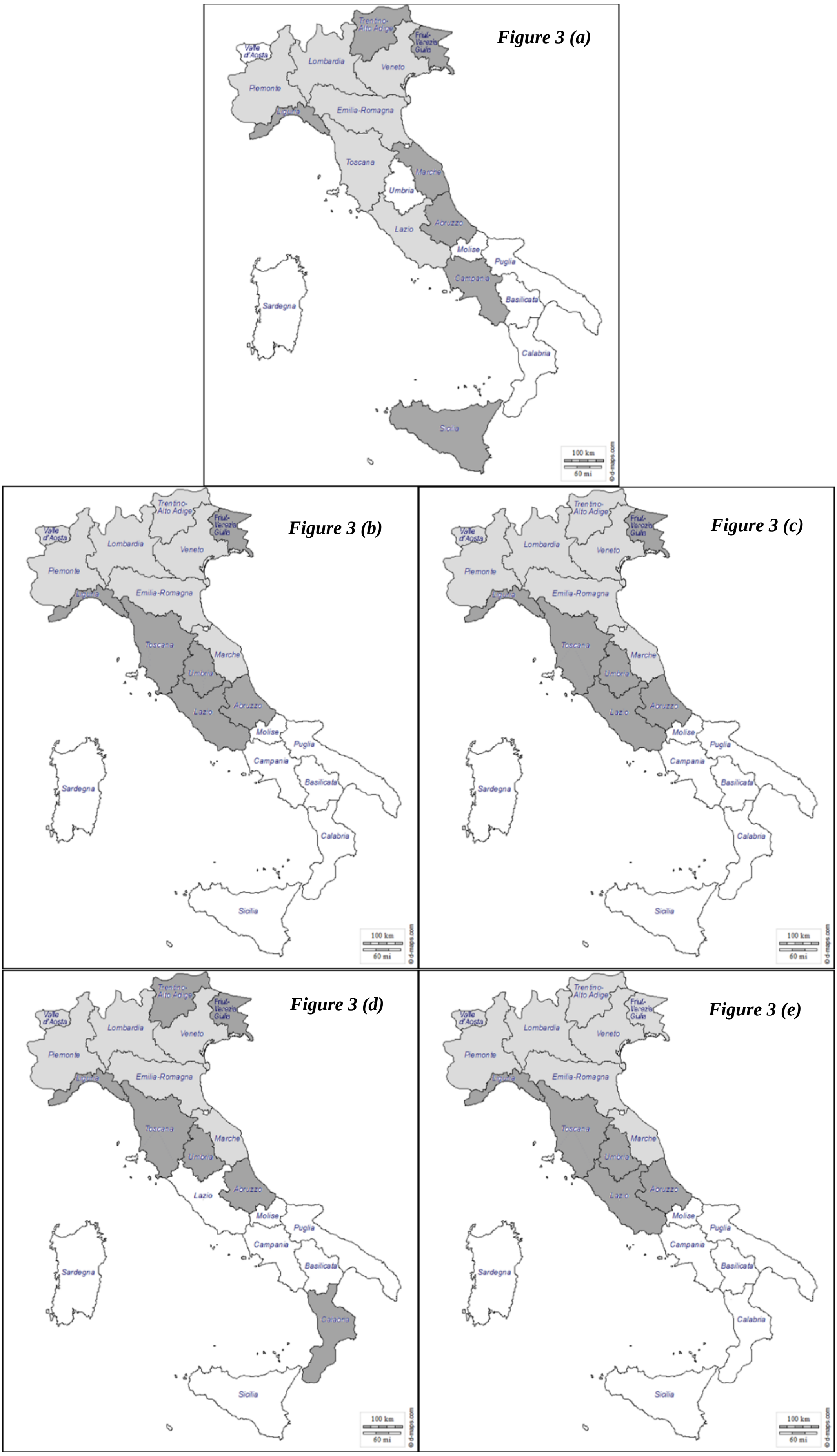
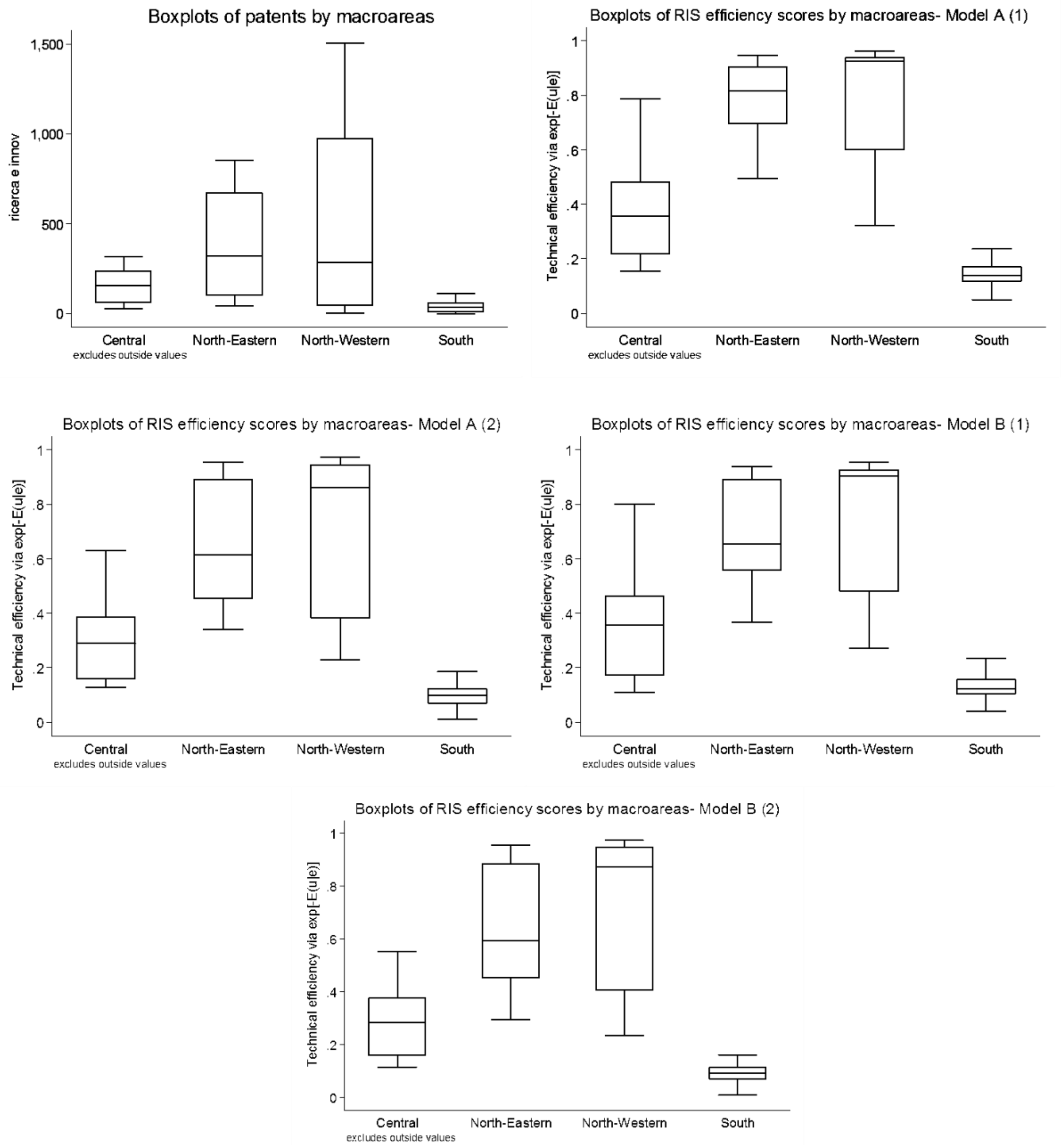


Figure 3(a) shows the number of patents
Figure 3(b)-3(c) shows RIS efficiency scores when R&D expenditures are used as innovative inputs (see Model A in Table 1 and Column 1 in Table 6)
Figure 3(d)-3(e) shows RIS efficiency scores when R&D employees are used as innovative inputs (see Model B in Table 1 and Column 1 in Table 8)
In white, regions within the first tertile; in dark grey, regions within the second tertile; in light grey, regions within the third quartile.

Figure 4 – Patents and RIS efficiency scores, by macroareas



Model A (1) refers to RIS efficiency scores when R&D expenditures are used as innovative inputs with the imposition of the linear homogeneity of degree 1 in inputs (see Model A in Table 1 and Column 1 in Table 6);
Model A (2) refers to RIS efficiency scores when R&D expenditures are used as innovative inputs without the imposition of the linear homogeneity of degree 1 in inputs (see Model A in Table 1 and Column 5 in Table 6);
Model B (1) refers to RIS efficiency scores when R&D employees are used as innovative inputs with the imposition of the linear homogeneity of degree 1 in inputs (see Model B in Table 1 and Column 1 in Table 8);
Model B (2) refers to RIS efficiency scores when R&D employees are used as innovative inputs without the imposition of the linear homogeneity of degree 1 in inputs (see Model B in Table 1 and Column 5 in Table 8).