Disentangling regional innovation capability: What really matters?

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ABSTRACT

Where does innovation come from? And do all regions innovate similarly? We deal with these questions by highlighting the complexity of the concepts of innovation capability and performance, and by testing their association at the European Union regional level. We disentangle inputs of innovation capability, and consider regional heterogeneity in institutional quality, to understand the relative endowment of what innovation inputs is associated with higher relative innovation performance. We find that 'formal' inputs – public and business R&D expenditure – do not work unconditionally and everywhere, and that less 'formal' ones – e.g., non-R&D expenditure and firms collaborating for innovation – matter particularly in regions with relative low-quality institutions. Moreover, institutional quality emerges as an innovation productivity-enhancing factor.

KEYWORDS

Innovation capability; innovation performance; institutional quality; regions; European Union

JEL CODES

O3; O52; R11

1. Introduction

Scholars from various disciplines – from economics to regional science, from management to economic geography –, policymakers at different governance levels, and practitioners have traditionally been interested in the role played by innovation as an engine driver for economic growth, dynamism, and competitiveness. This interest has led to both the identification of theoretical mechanisms for innovation to push the economic performance of firms and their territories, and the emergence of firm-, region-, and country-level research streams testing empirically the sources and returns of innovation performance.

Despite the large number of theoretical and empirical scholarly contributions on the topic, a critical and deep analysis of the basic concepts of innovation capability and innovation performance is still scarce. Similarly, little attention has been paid, from a conceptual viewpoint, to the proper definition, operationalisation, and measurement of the input or capability side of innovation in comparison with the output or performance side (e.g., Janger et al. 2017; Edquist et al. 2018; Hauser et al. 2018).

Our contribution to this debate is twofold. First, from a theoretical viewpoint, we discuss critically both the conceptual bases of the constructs of innovation capability and performance, and the drawbacks related to their operationalisation and measurement, also in light of the implications that the complexity of these (theoretical and empirical) dimensions may have for policy design and implementation. Second, we complement the theoretical discussion with a simple but original empirical exercise aimed at deepening the association between innovation capability – i.e., the input side of innovation – and innovation performance – i.e., the output side of innovation. We focus on the European Union (EU) regional context, given the emphasis put by European institutions on innovation as a key driver for territorial growth, convergence, integration, and competitiveness (e.g., the Horizon 2020 strategy). To this aim, we rely on the 2017 Regional Innovation Scoreboard (RIS) dataset to disentangle empirically the concepts of innovation capability and performance, and to evaluate the role of different input-side dimensions of the innovation process bearing in mind their high heterogeneity – from business expenditure in research and development (R&D) to high-educated population. We also account explicitly for regional differences in institutional quality to identify different best-fitting sets of innovation inputs, also shedding light on the apparent incapacity of some regions to translate their inputs endowment into maximised innovation output.

The rest of the paper is organised as follows. Section 2 discusses theoretically the concepts of innovation capability and performance drawing from the firm-level innovation literature. Section 3 extends the theoretical arguments to the regional level, and introduces the role of institutional quality as a potential structural factor influencing the association between innovation capability and performance. Section 4 presents the empirical framework, while Section 5 presents the empirical results. Section 6 concludes the works by discussing the empirical evidence, and drawing some policy implications.

2. Firm innovation capability: an unambiguous construct

The terms 'capability' or 'capacity' are unambiguous when referring to the firm. This emerges clearly from the way capabilities are framed in the resource-based view, which assumes the firm as a bundle of resources and related capabilities, that are unevenly distributed across competitors (Wernerfelt 1984; Barney 1991). The resource-based perspective makes it clear the distinction between these assets and the competitive performance resulting from their use, as measured, for example, by firm growth. Capabilities and performance remain separate constructs when moving from capabilities in general to specific functional capabilities – e.g., marketing, production, human resources management. This distinction is not lost even when we look at the more complex domain of innovation, and we focus on a typically multi-faceted construct such as innovation capability. In fact, although different definitions of innovation capability (or capacity) at the firm level have been proposed, they all indicate that it is a potential for innovation (e.g., Lawson and Samson 2001; Romijn and Albaladejo 2002).

Clearly, measuring innovation capability by taking into account its multi-dimensional nature is quite complex. As pointed out by Adams, Bessant, and Phelps (2006), studies on the management of innovation have drastically reduced complexity, often choosing a single variable that best represents innovation capability.

The most widely used measure of innovation capability is R&D intensity, typically expressed as the ratio between expenditure or employees in R&D and a measure of firm size, such as sales (Adams, Bessant, and Phelps 2006). Many studies have analysed the firm-level relationship between R&D intensity and (innovation) performance (Adams, Bessant, and Phelps 2006). However, R&D intensity is far from being a perfect proxy for innovation capability, as it does not represent properly the innovation capability of small firms (Kleinknecht 1987; Rammer, Czarnitzki, and Spielkamp 2009). For this reason, various alternative proxies for firm-level innovation capability have been proposed in the literature, among which the number of people committed to innovation – beyond R&D employees – relative to total employment, and the propensity to innovate extended to all the employees of the firm (Adams, Bessant, and Phelps 2006). Other contributions have relied on a set of objective variables, or a composite index, rather than on a single measure of the firm's innovation capability (e.g., Romijn and Albaladejo 2002; Carayannis and Provance 2008). In any case, the variables selected by scholars to measure innovation capability are placed on the input side of the firm's innovation process.

Patents held by a company at a certain time, or filed during a certain period, are a proxy for innovation performance frequently used in firm-level innovation studies, similarly to R&D intensity used as a proxy for innovation capability (Adams, Bessant, and Phelps 2006). The two variables also suffer from the same limits (Romijn and Albaladejo 2002). In addition, patenting is aimed at protecting inventions, but an invention does not turn into a process or product innovation necessarily (Archibugi 1992). Finally, patenting means coding the knowledge created in the innovation process, and making it accessible to potential imitators, but not all innovators are willing to take this risk (Rivkin 2001). In short, not all patents are innovation-related, and not all innovations are patentable or patented (Archibugi and Pianta 1996).

Alternative measures to the number of patents are the number of process innovations developed, or the number of products launched by the firm in a given period (Adams, Bessant, and Phelps 2006; Dziallas and Blind 2015). After the starting of the Community Innovation Survey (CIS) in the early 1990s, an increasing number of studies concerning one or more European countries has used dichotomous variables related to four types of innovation: product, process, organisational, or marketing innovation (Arundel and Smith 2013). Another interesting variable included in the CIS, and widely used in empirical studies on innovation (e.g., Leiponen 2005; Cainelli, De Marchi, and Grandinetti 2015), is the percentage of the firm's turnover from new products introduced during the last three years, and that were new to the market or to the firm. As for innovation capability, also innovation performance has been operationalised through a set of variables, composite indexes, or a combination of the two.

3. Regional innovation capability: an ambiguous construct

3.1. From firm- to region-level innovation capability

Following the firm-level innovation literature, the variable most frequently used as a proxy for the innovation performance of a territory is the number – somehow normalised – of patents held or filed by local firms and institutions (Brenner and Broekel 2011). This choice stems from the availability of patent data, and has its roots in the studies of distinguished economists, such as Scherer (1965). In the mid-eighties, Pavitt (1985, 82) established that "national differences in the total volume of domestic patent activity might be expected to reflect national differences in the volume of innovative activities". It should be noted that Pavitt (1985) considered patents as a proxy measure of innovative activities, adding that they should be placed on the output side of these activities, although being not necessarily a final output. Subsequently, several studies have moved in this direction (e.g., Acs, Anselin, and Varga 2002; Furman, Porter, and Stern 2002; Faber and Hesen 2004; Krammer 2009; Li 2009; Buesa, Heijs, and Baumert 2010; Choi, Lee, and Williams 2011).

As already mentioned, the likelihood that a firm will protect the innovation it has achieved through patenting differs according to its sector and size, among other characteristics. This evidence should be taken into account when comparing the innovation performance of two firms, two sectors, and, even more, two territories on the basis of the patenting activity. Even with this limitation, measuring the innovation performance of countries or regions with patents is a conceptually correct choice, as patents can be considered as an expression of their innovation capability. This is clearly stated by Furman, Porter, and Stern (2002, 905), who define the national innovative capacity as a "country's potential – as both an economic and political entity – to produce a stream of commercially relevant innovations". Following Porter's (1990) influential book on the competitive advantage of nations, Furman, Porter, and Stern (2002) measure the national innovation capacity through a number of variables related to three categories: the common innovation infrastructure, incorporating the overall size of R&D employment and spending; the cluster-specific innovation environment, with clusters defined on a national base; and the linkages between the common innovation infrastructure and industrial clusters. Thus, they capture the national innovation capacity only through factors that can be placed on the input side of innovation processes, and analyse their impact on a visible innovation output, namely the number of patents granted to inventors from a particular country.

During the last two decades, many authors have addressed the problem of how to measure national or regional innovation capability, and have grasped the intrinsic systemic complexity of the construct by avoiding to represent it with a single global measure. To this aim, evaluation systems based on a more or less large number of variables have been developed. However, several contributions have represented national or regional innovation capability with sets of variables, some of which can be placed on the input side, while others on the output side. Drawing on the information contained in the CIS and/or other statistical sources, several studies have used input variables – such as R&D expenditure as percentage of gross domestic product (GDP), or the incidence of firms with in-house R&D activities – together with output variables – such as the share of a region's patents in Europe, or the incidence of firms that have introduced some kind of innovation – to assess and compare the innovation capability of regions belonging to EU countries (e.g., Navarro et al. 2009; Pinto 2009; Capello and Lenzi 2013) or a single EU country (e.g., Evangelista et al. 2002; De Marchi and Grandinetti 2017).

The same mixture of input and output variables is found in the various national or regional innovation indexes that have been developed to support the innovation policies adopted at different governance levels, and later used also in scientific research (Hauser et al. 2018). Two of the most frequently used composite indexes are the European Innovation Index, developed at the initiative of the European Commission as a key element of the Lisbon Process (Schibany and Streicher 2008), and the Regional Innovation Index (RII), derived from the previous one, but based on a more limited number of indicators (Trippl, Asheim, and Miörner 2016).

In particular, the RII is calculated as the un-weighted average of the normalised scores of 18 indicators, ranging from 'pure' input indicators, such as the percentage of population aged 30-34 with post-secondary education, or the R&D expenditure in the business sector as percentage of GDP, to 'pure' output indicators, such as European trademark applications per billion GDP, or the sales – for small- and medium-sized enterprises (SME) only – of new-to-market and new-to-firm innovations as percentage of total turnover (Hollanders and Es-Sadki 2017).[1] The RII has been proposed to assess the innovation performance of European regions, and to classify them into four performance groups: leaders, strong innovators, moderate innovators, and modest innovators. In the regional innovation literature, the RII has been used to assess both the innovation performance of regions (e.g., De Noni, Orsi, and Belussi 2018), and their innovation capability (e.g., Pavão, Couto, and Natário 2019). However, since the index is a mixture of innovation capability and innovation

[1] The RII is defined based on 18 indicators that have been normalised according to a min-max approach, after a square root transformation has been applied to correct for skewness when necessary – see Hollanders and Es-Sadki (2017) for details.

performance indicators, it is not actually suitable to represent either the first or the second dimension (Edquist et al. 2018).[2]

Thus, it is needed to acknowledge the complexity to be faced when the concept of innovation capability is associated with a regional territory, even if the level of complexity depends on the more or less systemic nature of the innovation processes that involve it (Cooke 2001). This complexity makes it essential to build methodologies for assessing innovation capability that account for multiple aspects (Furman, Porter, and Stern 2002; Schiuma and Lerro 2008; Hauser et al. 2018). From this viewpoint, the wealth of information contained in the RIS makes it a very useful tool. If, however, a synthesis is sought through a composite index on innovation that brings together the capability and performance dimensions (i.e., the RII), there is the risk to draw a strongly distorting regional innovation landscape. This is not a purely academic problem, but one rich in innovation policy implications, as Hauser et al. (2018, 44) recently pointed out: "A mix of drivers and outcomes of innovation activities in one index impedes the prediction and analysis of effects of driving forces on outcomes and thereby complicates or impedes the identification of effective policy measures". This leads to the use of a dataset such as the RIS, that allows us to separate the innovation inputs (drivers) – that, taken together, are representative of the innovation capability of regions – from the innovation outputs – that, taken together, are representative of their innovation performance –, in order to explore the link that exists between these two dimensions. This is the focus of our empirical exercise. In addition, we chose to disentangle the input-side dimension of regional innovation in light of the deep internal heterogeneity that characterises it (Edquist et al. 2018).

3.2. Regional innovation and institutional heterogeneity

[2] The same is true for the more recent and selective Innovation Output Indicator introduced by the European Commission with the aim of supporting "policy-makers by offering an output-oriented measure of innovation performance at the country and EU levels" (Vértesy and Damioli 2020, 9). However, this index combines output variables (e.g., the number of patent applications per billion GDP) and input variables (e.g., the number of persons employed in knowledge-intensive business industry within total employment).

The complexity characterising the proper definition, operationalisation, and measurement of the concepts of regional innovation capability and performance concerns also the specificities of the territorial contexts where innovation processes take place. Structural and systemic differences emerge not only among countries, but also among regions within a country, and this is particularly relevant in the EU, where countries and regions with different historical roots, cultures, institutional backgrounds, resource endowments, and development levels coexist within an economically and politically integrated area. In such a scenario, it is highly unlikely that homogenous innovation policies defined through a 'one-size-fits-all' approach to the assessment of regional innovativeness do work effectively, given the level of complexity and geographic heterogeneity (e.g., Farole, Rodríguez-Pose, and Storper 2011).

In this respect, a critical point that has been highlighted more recently concerns the role of the local institutional context where innovation processes take place, i.e., the regional institutional framework that defines the 'environment' where economic actors operate, and transform innovation inputs into innovation outputs (e.g., Storper 2005; Christopherson and Clark 2007; Rodríguez-Pose and Di Cataldo 2015). The idea is that regional systems characterised by high-quality institutions are likely to perform better because of reduced corruption, less bureaucratic inefficiency, higher efficiency and effectiveness of local governments, and more transparency. In this sense, institutional quality can play a key role in setting the 'rules of the game' of a society (e.g., North 1990; Rodríguez-Pose and Storper 2006; Rodríguez-Pose 2013), and, thus, in creating a 'fertile environment' for innovation inputs to be maximised into innovation outputs.

At the same time, however, it could also be that regional institutional quality does not influence the innovation process homogeneously with respect to the different innovation inputs (e.g., Crescenzi, Rodríguez-Pose, and Storper 2007). Indeed, 'formal' inputs, such as public and business R&D expenditure, can require some degree of 'institutional warranty' for being maximised, while less 'formal' ones, such as inter-firm collaborations, could work even in the absence of a strong institutional framework. For example, very high levels of institutional quality could be necessary for public R&D expenditure to become effective, thus to avoid that investments in R&D activities are wasted or lost. On the contrary, SMEs' collaborating in the innovation process could be successful also in local contexts where institutions do not work effectively, and, maybe, it is right in response to 'institutional drawbacks' that innovation-based inter-firm networks emerge "as an adaptive response to environmental uncertainties" (Ozman 2009, 44).

It follows that different institutional contexts can be characterised by – and influence the development of – different approaches to the innovation activity. Thus, regional heterogeneity in institutional quality can help understanding not only the different innovation paths undertaken by regional systems across the EU, but also how regions with 'structural' differences – for example, in terms of institutional setting – could be able to identify and exploit their best-fitting set of innovation inputs in order to maximise their innovation capability and, consequently, their innovation performance.

3.3. Regional innovation inputs and regional innovation performance

Our contribution differs from previous ones criticising the use of synthetic indexes combining the input and output sides of the innovation process to assess and compare the innovation performance of territories, such as those of Edquist et al. (2018) and Hauser et al. (2018). Edquist et al. (2018) look at the country-level Innovation Union Scoreboard, and propose to use the ratio of innovation outputs to innovation inputs as an innovation performance (i.e., productivity) measure, rather than an index mixing innovation outputs and inputs. They are interested in comparing the ranking of EU Member States according to the two measures, and find profound differences. Similarly to us, Hauser et al. (2018) look at the EU regional context, but base their critique to the use of composite indexes combining innovation outputs and inputs – particularly, the RII – on a 'statistical' argument, highlighting how a synthetic index of innovation performance could work properly only if the different innovation inputs affect similarly the different innovation outputs. They also provide empirical evidence on the relationship between a set of innovation inputs and a set of single and composite innovation output measures. On the contrary, we develop a theoretically-driven critique to the use of composite indexes to assess regional innovation performance by extending firm-level arguments to the regional dimension.

Furthermore, our empirical exercise aims at assessing, first, the association between relative inputs endowment and relative innovation performance, and, second, whether 'structural' regional conditions – particularly, institutional quality – help explaining why different inputs do not work everywhere, as well as regions' constraints to maximise their inputs endowment to produce innovation output. With respect to this last dimension, our contribution differs also from previous regional innovation studies accounting for the institutional dimension. For example, Rodríguez-Pose and Di Cataldo (2015) analyse the direct role played by regional institutional quality on regions' patents growth rate within a 'standard' knowledge-production function framework. On the contrary, we are interested in – and evaluate empirically – the indirect role of institutional quality as a factor able to 'activate' – and stimulate the productivity of – different innovation inputs.

4. Empirical framework

4.1. The dataset

Regional innovation data are drawn from the 2017 edition of the RIS, that is provided by the Directorate-General for Internal Market, Industry, Entrepreneurship and SMEs of the European Commission. The RIS 2017 dataset covers the 28 EU Member States, plus Norway, Serbia, and Switzerland, and provides information on region-level innovativeness in the form of 18 indicators – that are originally used to calculate the synthetic RII aimed at assessing the relative innovation performance of territories – capturing both the input and output sides of innovation (Hollanders and Es-Sadki 2017).

Drawing on the available RIS data, we have first classified the 18 indicators into two groups aimed at capturing the dimensions of innovation output, as a proxy for innovation performance, and innovation input, as a proxy for innovation capability, respectively. In this respect, our operationalisation strategy differs substantially from that adopted by Hollanders and Es-Sadki (2017), who combine the different indicators into a synthetic index of regional innovativeness, and is built on the approach proposed by Edquist et al. (2018). Table 1 reports the original 18 indicators, their definition, and the adopted classification. Following Edquist et al. (2018), we have included the following indicators in the output side of innovation: those capturing the final or an intermediate step of the innovation process (trademarks, designs, patents), SMEs' propensity to introduce (product, process, marketing, organisational) innovations, SMEs innovating in-house (i.e., SMEs that have introduced product or process innovations either in-house or in combination with other firms), and the presence of innovative or mid- and high-tech products in the market (i.e., SMEs' sales of new-to-market and new-to-firm innovations, and exports of mid- and high-tech manufacturing products).[3] The input side of innovation has been defined considering the remaining indicators, that capture public R&D expenditure, business R&D expenditure, SMEs' non-R&D expenditure for innovation, SMEs collaborating for innovation, human capital (captured by the percentage of population aged 30-34 years with post-secondary education), lifelong learning (as a proxy for continuous training), employment in mid- and high-tech manufacturing (MHTM) and knowledge-intensive services (KIS) sectors, and scientific publications. In particular, the three indicators for most-cited publications, public-private co-publications, and international scientific co-publications have been aggregated into a synthetic index capturing scientific publications.

[Table 1 about here]

We have then enriched the regional innovation dataset with region-specific data on institutional quality drawn from the 2013 wave of the European Quality of Government Index (EQGI) dataset provided by the Quality of Government Institute (University of Gothenburg). The EQGI dataset consists of individual-level information referring to the year 2012, and derived from a

[3] Following the mainstream of innovation literature, we consider patents as an indicator of innovation output. However, as emerged in the theoretical sections, patenting is not always linked to innovation, and not all innovations are patented. These limitations convinced Edquist et al. (2018) to exclude patents from their list of innovation outputs.

citizen-based survey – covering 85,248 citizens residing in 206 regions – on the perception and experience of individuals with respect to corruption, quality, and impartiality in terms of education, public health care, and law enforcement in their own region (Charron, Lapuente, and Rothstein 2013; Charron, Dijkstra, and Lapuente 2015). Finally, the dataset has been integrated with region-specific data series for GDP, population, employment, unemployment rate, and land area provided by Eurostat.

We have cleaned the datasets by keeping only EU countries for which both innovation and institutional data series were available, and presenting a sub-national geographic division. In addition, given the different geographic coverage characterising the RIS and EQGI datasets, we have re-aggregated the data series, when necessary, in order to match the different levels of the *Nomenclature des Unités Territoriales Statistiques* (NUTS) employed in the two datasets, while trying to maximise the number of regions covered and the geographic heterogeneity of the sample. The cleaning procedure left us with a cross-sectional sample of 194 regions from 20 EU countries. The sample includes NUTS-1 regions for Austria, Belgium, Bulgaria, France, and the United Kingdom, while NUTS-2 regions are considered for the remaining countries.[4] All countries in the sample are covered entirely, except for the German region of Chemnitz, and the Portuguese

[4] The cleaning procedure of the RIS and EQGI datasets has consisted in the following steps. First, we have excluded from the sample non-EU countries (Norway, Serbia, Switzerland, Turkey, and Ukraine) despite them being included in either one of both datasets, as the analysis focuses on the EU. Second, we have excluded from the sample EU countries not included in either one or both datasets, as well as EU countries for which data were available at the country level only, namely Cyprus, Estonia, Latvia, Lithuania, Luxembourg, Malta, and Slovenia. Third, given the different geographic coverage characterising the RIS and EQGI datasets with respect to a sub-sample of countries, we have re-aggregated the data series in order to match the different NUTS levels employed in the two datasets. Both datasets provide information at NUTS-1 level for Belgium and the United Kingdom, while at NUTS-2 level for Czech Republic, Croatia, Denmark, Italy, the Netherlands, Poland, Portugal, Republic of Ireland, Romania, Slovak Republic, and Spain. On the contrary, the two datasets consider different geographic levels for the remaining countries. On the one hand, the availability of individual-level data in the EQGI dataset has allowed us to re-aggregate the data series at the NUTS-2 level by weighting for population shares for those countries covered at NUTS-1 level in the EQGI dataset but at NUTS-2 level in the RIS dataset – namely, Germany, Greece, Hungary, and Sweden. On the other hand, the unavailability of micro data in the RIS dataset – that provides indicators already aggregated at the regional level – has prevented us from considering the NUTS-2 level in those countries covered at NUTS-2 level in the EQGI dataset but at NUTS-1 level in the RIS dataset – namely, Austria, Bulgaria, and France. Fourth, Finland has been excluded from the sample, despite being covered by both datasets, because the two datasets employ different NUTS classifications, and this prevented us from obtaining a reliable matching of the two regional data series given the changes that occurred between the 2006 NUTS taxonomy employed in the EQGI dataset and the 2013 NUTS taxonomy employed in the RIS dataset for Finland. Finally, GDP, population, employment, unemployment rate, and land area data have been drawn from Eurostat at the appropriate NUTS level.

autonomous regions of Azores and Madeira due to data availability issues – see Table A1 (Online Supplementary Material) for the structure of the sample.

4.2. Definition of the variables

The empirical analysis aims at assessing the statistical association between the input and output sides of innovation activity in EU regions. Specifically, we aim at disentangling the role played by different innovation inputs on an aggregate innovation output measure, also accounting for cross-regional heterogeneity in institutional quality as a moderating factor.

The dependent variable capturing regional innovation output (i.e., regional innovation performance) is defined as the average value of the eight indicators that have been presented previously in Table 1. Given that all the indicators available in the RIS dataset are defined according to a $[0,1]$ distribution, the dependent variable capturing regions' relative innovation output ($Innovation\ Output_r$) has been defined by adopting the same normalisation procedure, thus making it ranging in the interval $[0,1]$ over the cleaned sample of 194 regions.

The same rationale has been employed to operationalise also the input side of regional innovation. First, we have defined a synthetic measure of innovation input as the average value of the eight indicators previously identified as inputs in Table 1. Then, this synthetic measure of innovation input has been normalised in the interval $[0,1]$ over the cleaned sample in order to define a variable capturing the relative 'overall' innovation capability of a region ($Innovation\ Input_r$). Second, we have disentangled the regional innovation capability dimension by considering the eight input indicators separately, in order to evaluate their individual contribution to the relative innovation performance of regions. Thus, each innovation input has been normalised in the interval $[0,1]$.

We have then constructed a synthetic measure of institutional quality at the regional level as the average value of three 'pillars' capturing the dimensions of quality, impartiality, and corruption of the local institutional environment. The EQGI survey questions are structured in such a way that they allow us to identify three main 'pillars' concerning the overall quality of the regional institutional context. Individuals are asked, concerning their own region, about: (i) the perceived quality of public education, health care system, and law enforcement, the perceived fairness of elections, and the perceived fairness and ability of media to report political corruption; (ii) the perceived impartiality in accessing public services (public education, health care), and of law enforcement; and (iii) the perceived corruption characterising public education, health care system, and law enforcement, and the own – and others' – experience with bribery in the public sector. This synthetic measure has been normalised in the interval $[0, 1]$ to obtain the variable for institutional quality ($Institutional\ Quality_r$) included in the empirical model.

Finally, we have defined a set of explanatory variables aimed at controlling for regional structural conditions: (i) GDP per capita, defined as GDP over population, to capture regional wealth; (ii) unemployment rate, to capture regional labour market conditions; (iii) employment density, defined as employment per square kilometre, to capture agglomeration-related forces; (iv) population, to control for regional size heterogeneity. These four variables have been normalised in the interval $[0, 1]$ for the sake of operational coherence.

Tables 2 and 3 report some descriptive statistics of the dependent and explanatory variables, and the correlation matrix of the explanatory variables, respectively.

[Table 2 about here]

[Table 3 about here]

4.3. Econometric approach

The empirical analysis aims at assessing the relationship between a battery of innovation inputs and a synthetic measure of innovation output at the regional level. Specifically, given the normalisation approach adopted to define the input- and output-side innovation variables, our goal is to evaluate whether the relative endowment in a particular innovation input is associated with a higher relative endowment in innovation output, i.e., with a better relative innovation performance. Thus, by considering a series of innovation inputs – and, particularly, those accounted for by the European policymaker to assess regions' innovativeness and, consequently, define the EU regional innovation policy –, our primary aim is to assess what inputs are more relevant in explaining a relative high ranking of regions in terms of innovation performance.

Given the bounded nature of the dependent variable for innovation output, we have relied on a fractional response model to test the statistical association between innovation inputs and innovation output. Let y_r be the dependent variable for innovation output in region $r = 1, \dots, 194$, such that $0 \leq y_r \leq 1$, and let $\boldsymbol{x_r}$ be a $1 \times K$ vector of explanatory variables, then the fractional probit model can be specified as follows (Papke and Wooldridge 1996):

$$E(y_r|\boldsymbol{x_r}) = \Phi(\alpha + \boldsymbol{x_r}\boldsymbol{\beta}) \qquad (1)$$

where $\Phi(\cdot)$ denotes the standard normal cumulative distribution function, α denotes the constant term, and $\boldsymbol{\beta}$ denotes the vector of parameters to be estimated.

Equation (1) can be made more flexible by relaxing the assumption that the error distribution of the latent model has a unit variance. This consists in specifying the variance as a function of the explanatory variables in the regression model, excluding the constant term, such that the heteroskedastic fractional probit model (HFPM) can be specified as follows:

$$E(y_r|\boldsymbol{x_r}) = \Phi[(\alpha + \boldsymbol{x_r}\boldsymbol{\beta})/\exp(\boldsymbol{z_r}\boldsymbol{\gamma})] \qquad (2)$$

where $\boldsymbol{z_r}$ is a $1 \times M$ function of the vector $\boldsymbol{x_r}$ of explanatory variables, $\boldsymbol{\gamma}$ is the vector of associated parameters, and all the other terms are defined as before. Having estimated Equation (2), we can then test for the null hypothesis of homoskedastic variance ($\mathrm{H_0}\colon \boldsymbol{\gamma} = 0$) using a simple Wald test.

5. Empirical results

5.1. Main results

Table 4 reports the average marginal effects obtained from the estimation of a series of HFPMs – see Table A2 (Online Supplementary Material) for the full sets of estimated coefficients. Specifically, specifications (1) to (4) do not account for the potential moderating role played by institutional quality, which is instead accounted for in specification (5).

First, it is worth noting that the Wald test rejects the null hypothesis of homoskedastic variance in all the estimated specifications. Second, looking at specifications (1) to (3), the results suggest that, overall, a positive association exists between regions' relative innovation inputs endowment and their relative innovation performance. However, more interesting insights emerge when disentangling the input-side of regional innovation – see specification (4). A relatively higher innovation performance is mainly associated with a relatively higher endowment of business R&D expenditure, i.e., the 'formal' innovation input mostly emphasised as a key driver for innovation, but also less 'formal' inputs emerge as relevant drivers of regions' innovation performance: SMEs' non-R&D expenditure for innovation, SMEs collaborating for innovation, a region's endowment of labour force in MHTM and KIS sectors, and, to a lower extent, the production of scientific publication. On the contrary, input-side dimensions such as public R&D expenditure, human capital, and lifelong learning seem to be in a negligible association with regional innovation performance.

[Table 4 about here]

5.2. Regional heterogeneity and the moderating role of institutional quality

As underlined by Hollanders and Es-Sadki (2017), the geography of innovation in the EU is characterised by high heterogeneity, and it seems that not all regions are able to maximise their inputs endowment to produce innovation output. First, there is a club of high-innovative territories in the EU geographic 'core', while innovation performance tends to dissolve moving toward more peripheral areas. Moreover, within-country variability in innovation performance is rather than homogenous: countries characterised by a relatively low level of regional heterogeneity (e.g., Austria, Bulgaria) coexist with others characterised by quite important internal differences (e.g., Germany, Spain, Italy, Portugal) – see Figures A1 and A2 (Online Supplementary Material). A similar pattern characterises also the input side of regional innovation, although the core-periphery divide seems to be less pronounced. In fact, regions relatively high-endowed with innovation inputs are located also in less central areas (e.g., Northern regions in Sweden, Mediterranean regions in France), while their relatively low-endowed counterparts can be spotted also in the EU geographic 'core' – see Figures A3 and A4 (Online Supplementary Material).

Second, and more importantly, regions relatively high-endowed with innovation inputs are not necessarily among the most innovative ones in terms of innovation output, and vice versa. This clearly emerges from Figure 1, that plots the distribution of regions with respect to the output and input sides of innovation, and allows us to identify four groups of regions. First, a group of 80 regions – representing the 41.2% of the sample – characterised by levels of both innovation inputs and innovation output above the sample average, i.e., regions that are relatively high-endowed with innovation inputs and able to rank relatively high in terms of innovation performance. Second, a group of 77 regions – representing the 39.7% of the sample – characterised by levels of both innovation inputs and innovation output below the sample average. Third, 14 regions – representing the 7.2% of the sample – lie below the sample average in terms of relative innovation performance, despite being relatively high-endowed with innovation inputs. Examples of this pattern are given by the Swedish region of Övre Norrland – ranked 109^{th} (15^{th}) in terms of innovation output (input) –, and the Slovak region of Bratislava – ranked 126^{th} (37^{th}) in terms of innovation output (input). Finally, 23 regions – representing the 11.9% of the sample – are relatively low-endowed with innovation inputs, but lie above the sample average in terms of innovation performance. Examples are the German region of Koblenz, that ranks 12th in terms of innovation output, while only 137th in terms of innovation input, and the Italian region of Veneto, that ranks 27th (116th) on the output (input) side of innovation.

[Figure 1 about here]

Thus, while some regions that are relatively poor-endowed of inputs are able to rank among the most innovative EU territories, others seem unfit to translate a relative high-level inputs endowment into a relative great innovation performance. These stylised facts also corroborate the idea that a synthetic index combining input and output dimensions – such as the RII – does not capture properly the relative innovation performance of regions. Considering the previous examples, Koblenz and Veneto would be ranked 81st and 75th, respectively, according to a synthetic index of input and output indicators (94th and 128th, respectively, out of 220 regions according to the RII), despite showing a relative high ranking in terms of innovation output.[5]

Regional heterogeneity in institutional quality can help understanding this 'contradiction'. To this aim, we have augmented the baseline model by adding a set of interaction terms between the institutional quality variable and the vector of innovation inputs. Specification (5) in Table 4 reports the average marginal effects obtained from the estimation of this augmented version of the baseline model – see specification (5) in Table A2 (Online Supplementary Material) for the full sets of estimated coefficients. Overall, the results confirm those reported in specification (4) in Table 4. Indeed, a relatively higher innovation performance is mainly associated with a relatively higher endowment of business R&D expenditure, non-R&D expenditure for innovation, SMEs collaborating for innovation, labour force in MHTM and KIS sectors, and scientific publications.

[5] Our synthetic index combining input and output indicators reflects quite well the RII. For example, Stockholm (Sweden) and Hovedstaden (Denmark) are ranked 1st and 2nd, respectively, according to both our synthetic index and the 2017 RII (when excluding non-EU countries), while the Romanian regions of Sud-Vest Oltenia and Nord-Est occupy the penultimate and last position, respectively, according to both indexes.

A clearer picture emerges looking at Table 5, which reports the estimated marginal effects of the innovation inputs at selected percentiles of the distribution of the institutional quality variable, and allows us to properly evaluate the moderating role played by institutional quality – these results are derived from specification (5) in Table A2 (Online Supplementary Material). The results unveil the existence of two clear patterns of innovative behaviour. Regions characterised by high-quality institutions seem to rely more on 'formal' innovation inputs – public and business R&D expenditure –, while regions characterised by low-quality institutions seem to rely on less 'formal' innovation inputs. Thus, it seems that different 'structural' conditions of regions – in terms of local institutional quality, at least – lead them to exploit different innovation inputs. In other words, our results suggest that the association between relative endowment of different innovation inputs and relative innovation performance depends on the relative position regions occupy in the territorial distribution of institutional quality.[6]

[6] We have performed several robustness exercises to check the main results. First, as there is not a full agreement in placing patents and SMEs innovating in-house on the output side of innovation, the baseline model and its modified version including the interaction terms between the variables for institutional quality and innovation inputs have been replicated by considering alternative dependent variables for innovation output defined by excluding the components capturing patents only, SMEs innovating in-house only, and both them. Table A3 (Online Supplementary Material) reports the estimated average marginal effects of the key explanatory variables for innovation inputs referring to both the baseline model – specifications (1) to (3) – and the augmented version accounting for the moderating role of institutional quality – specification (4) –, while Table A4 (Online Supplementary Material) reports the estimated marginal effects of the innovation inputs at selected percentiles of the distribution of the institutional quality variable obtained from specification (4) in Table A3. The main results presented in Tables 4 and 5 are fully confirmed. Second, the baseline model and its modified version including the interaction terms between the variables for institutional quality and innovation inputs have been augmented by a set of spatially lagged innovation input variables to account for local spatial spillovers, i.e., spillover effects occurring among adjacent regions, and driven by their relative endowment in innovation inputs (Capello 2009). Spatial lags of the 'overall' innovation input and the individual innovation input variables have been defined through a first-order contiguity row-standardised spatial weights matrix. The estimated average marginal effects of the key variables capturing 'overall' and individual innovation inputs, and their spatial lags, are reported in Table A5 (Online Supplementary Material). Specifications (1) and (2) do not account for the moderating role of institutional quality, which is accounted for in specification (3). The results concerning the own-region innovation inputs are in line with those obtained without accounting for local spillovers. These results are complemented by those presented in Table A6 (Online Supplementary Material), which reports the estimated marginal effects of the individual own-region innovation inputs at selected percentiles of the distribution of the institutional quality variable obtained from specification (3) in Table A5. The results confirm the patterns observed in Table 5. Third, given the relatively high correlation between the institutional quality and individual innovation input variables, we have tested for the moderating role of institutional quality by avoiding the use of interaction terms. Specifically, we have split the sample around the median value of the distribution of the institutional quality variable, and we have replicated the main specification – i.e., specification (4) in Table 4 – for the two sub-samples of low- and high-quality regions. Although this exercise does not allow us to evaluate in detail the moderating role of institutional quality, it still allows us to assess whether different patterns of association characterise individual innovation inputs and innovation output for regions showing different relative institutional quality. The advantage of this exercise is that possible biases related to high correlations are relaxed. Table A7 (Online Supplementary Material) reports the estimated average marginal effects of the innovation input variables, and the results generally confirm the patterns observed when considering the moderating role of institutional quality through interaction terms. Finally, this last exercise has been performed by augmenting the empirical model with spatially lagged terms of the individual innovation inputs. The

[Table 5 about here]

5.3. Institutional quality and innovation productivity

The analysis presented in Sub-Section 5.2 has contributed to shed light on the 'contradiction' characterising some EU regions, i.e., the fact that territories relatively low-endowed with innovation inputs perform better than their relatively high-endowed counterparts, and vice versa. In this respect, institutional quality emerges as a factor able to explain the existence of different sets of innovation inputs working in different regions, such that, first, regions do not innovate in the same way, and, second, 'one-size-fits-all' policies would be sub-optimal.

However, this evidence tells little about regions' inability to maximise their input endowment into innovation output. This issue concerns explicitly the productivity dimension, i.e., a region's capacity to transform its (individual) innovation inputs endowment into innovation output, and institutional quality could emerge as a factor able to influence the regional innovation process. Indeed, high-quality local institutions are likely to favour the emergence of a regional environment where economic actors can maximise the available inputs into innovation output, thus improving regional innovation performance.

In order to assess whether this is the case, we have complemented our previous evidence on the role of institutional quality as a region-specific force able to 'activate' some innovation inputs by considering explicitly the productivity dimension. To this aim, we have poorly followed Edquist et al. (2018), who consider the "ratio of aggregate innovation outputs (numerator) to aggregate innovation inputs (denominator)" (198) as a "productivity, or efficiency-based, measure of innovation system performance" (204).

Drawing on this intuition, we have constructed a series of productivity indexes to be used as dependent variables in order to evaluate whether and to what extent institutional quality represents a

results of this exercise are reported in Table A8 (Online Supplementary Material), and generally confirm our previous results.

factor stimulating innovation productivity. The productivity index is defined as the ratio between the innovation output index and the innovation input index – both normalised in the interval $[0, 1]$ – , and is further normalised according to a $[0, 1]$ distribution (Edquist et al. 2018). Thus, its interpretation is straightforward: the lower is the value of the index, the lower is a region's relative performance, such that "if the input side is, relatively speaking, much larger than the output side, the performance of the system as a whole is low … [and] the efforts to produce or stimulate innovation have not led to a corresponding actual production of innovations" (Edquist et al. 2018, 200). Besides considering a measure of 'overall' productivity defined using the synthetic index capturing the input side of the innovation process as denominator, we have also constructed productivity indexes defined with respect to each individual input in order to disentangle the innovation productivity-enhancing role played by institutional quality. Each productivity index has been specified as a function of institutional quality – plus region-specific controls and country dummies –, and modelled through a HFPM.

Figure 2 summarises the results of this exercise by plotting the estimated average marginal effect (along with confidence intervals) of the institutional quality variable on the 'overall' and input-specific productivity indexes used as dependent variables (specified on the vertical axis), and also reports the value of the estimated average marginal effect in parentheses besides the name of each dependent variable – see Table A9 (Online Supplementary Material) for the estimated average marginal effects and the statistics referring to the estimated models. First, the results highlight that institutional quality is positively associated with 'overall' regional productivity. Second, it emerges that improvements in the relative quality of institutions are associated with relative higher productivity of public R&D expenditure, business R&D expenditure, SMEs collaborating for innovation, and labour force in MHTM and KIS sectors. On the contrary, it seems that institutional quality does not stimulate the productivity of the remaining inputs.

[Figure 2 about here]

These results not only corroborate the previous ones, but also highlight the role of institutional quality as a factor enhancing innovation productivity – related to some inputs, at least – , and, consequently, its relevance to improve regions' capacity to translate their innovation inputs endowment into innovation output. Therefore, our evidences confirm the attention put by the European policymaker on institutional quality as a dimension able to stimulate efficient resource allocation, and, consequently, innovativeness.

6. Discussion and conclusion

Our empirical analysis highlights some interesting insights that corroborate the theoretical discussion developed in the first part of this paper. First, the correlation between innovation capability (as a whole) and innovation performance is positive and statistically significant. However, behind this general result are the cloud of situations shown in Figure 1. In particular, a non-negligible number of regions relatively high-endowed with innovation inputs do not outperform their relatively low-endowed counterparts. This has relevant policy implications. In fact, innovation policies based on a 'one-size-fits-all' approach cannot account properly for regional specificities in terms of innovation inputs, and their conversion into a relevant output.

The second interesting result concerns the individual innovation inputs. We confirm the well-established positive link between business R&D expenditure and innovation performance. Moreover, our results unveil that less 'formal' inputs – such as SMEs' non-R&D expenditure for innovation, SMEs' collaborating for innovation, a region's endowment of labour force in MHTM and KIS sectors, and the production of scientific publication – play a quite relevant role. Instead, two traditionally-emphasised innovation drivers of regional innovation performance – namely, human capital and public R&D expenditure – are not correlated significantly with regional innovation performance. The negligible correlation between human capital and innovation performance can be related to problems such as low education attainment and low quality of education, as well as to a mismatch between educational supply and labour demand that emphasises the incapacity of regional labour markets to transform skills into innovation-related jobs (e.g., Rodríguez-Pose and Vilalta-Bufí 2005; Leuven and Oosterbeek 2011).

To grasp the negligible link between public R&D expenditure and innovation performance, one must bear in mind that, following Edquist et al. (2018), we have constructed the dependent variable capturing innovation output in such a way that it is unbalanced on the side of SMEs. Studies on innovation in European countries have largely stressed how universities (and research centres) engage mainly with large corporations (e.g., Cooke, Boekholt, and Tödtling 2000; Rõigas, Mohnen, and Varblane 2018). On the one hand, SMEs can lack the absorptive capacity needed to benefit from tapping into academic knowledge (Spithoven, Clarysse, and Knockaert 2010). On the other hand, universities often prefer to be involved in large business projects (Caloghirou, Tsakanikas, and Vonortas 2001), and do not seem to have invested much in the creation of an interface user-friendly for SMEs (Bodas Freitas, Marques, and de Paula e Silva 2013). Our empirical exercise corroborates these results, and suggests that increasing the relative endowment of public R&D expenditure is an ineffective policy to improve the relative innovation performance – particularly, SMEs' contribution to it – if it is not preceded and accompanied by robust actions to ensure that SMEs benefit from knowledge spillovers generated by public R&D efforts.

An interesting picture concerning the individual innovation inputs emerges when accounting for heterogeneity in institutional quality. Although the direct role of institutions and institutional quality has been investigated deeply in terms of productivity and economic growth, and, to a lower extent, also in terms of innovation performance, our knowledge is almost scarce on how institutional quality can shape the link between innovation capability and performance. This point highlights our third relevant result, i.e., that different innovation inputs do work differently in different institutional environments. This is a critical point, from both a theoretical and a policy perspective. From a theoretical viewpoint, our evidence highlights a further dimension of complexity characterising the definition, operationalisation, and measurement of innovation capability and performance, namely the contextual heterogeneity concerning the economic actors involved in the innovation process. This reinforces even more the idea that a synthetic index of 'regional innovativeness' cannot be enough to understand region-specific innovation systems. From a policy perspective, our evidence suggests that innovation policies – and regional policies, in general – should be tailored and region-specific in order to be effective in supporting regional innovation systems to transform their inputs endowment into innovation output – i.e., to maximise their innovation capability in order to improve their innovation performance.

In particular, our results suggest that more 'formal' inputs may require some quality of the institutional environment to become innovation drivers. This is the case of business R&D expenditure and, even more, of public R&D expenditure. On the contrary, regional systems seem to rely more on less 'formal' innovation inputs where low-quality institutions prevail. Thus, low-quality regional institutions can represent a disincentive for economic actors to invest in R&D activities, and to collaborate with public bodies (universities and research centres) in order to innovate and produce innovations. This explains also why the public side of the R&D activity becomes a relevant innovation input only in high-quality institutional contexts.

Finally, our analysis suggests that regional policies are needed to improve 'structural' dimensions – such as institutional quality – that contribute to the emergence of optimal conditions for regional systems to increase their innovation productivity, i.e., their capacity to maximise their inputs endowment in order to realise innovation output. However, tailored – rather than space-neutral – regional innovation policies are desirable, in light of the heterogeneity characterising the EU, and the existence of different regional innovative behaviours.

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Table 1. Definition and classification of RIS 2017 indicators.

RIS Indicators			Classification	
No.	Indicator	Definition	Output / Input	Aggregation
1	Patent Applications	Number of patents applied for at the EPO (by year of filing and inventor's address) per billion regional GDP in PPS	Output	…
2	Trademark Applications	Number of trademarks applied for at the EUIPO per billion regional GDP in PPS	Output	…
3	Design Applications	Number of designs applied for at the EUIPO per billion regional GDP in PPS	Output	…
4	Product or Process Innovators (SME)	Number of SMEs that introduced a new product or a new process to one of their markets as percentage of total SMEs	Output	…
5	Marketing or Organisational Innovators (SME)	Number of SMEs that introduced new marketing and/or organisational innovations to one of their markets as percentage of SMEs	Output	…
6	SMEs Innovating In-House	Number of SMEs with in-house innovation activities (introduction of new products/processes either in-house or in combination with other firms, excluding new products/processes developed by other firms) as percentage of total SMEs	Output	…
7	Sales of New-to-Market and New-to-Firm Innovations (SME)	Sum of total turnover of new or significantly improved products for SMEs as percentage of SMEs' total turnover	Output	…
8	Exports in Mid- and High-Tech Manufacturing	Sum of exports in mid- and high-tech manufacturing sectors as percentage of total manufacturing exports	Output	…
9	Research and Development (R&D) Expenditure of the Public Sector	All R&D expenditures in the government sector and the higher education sector as percentage of regional GDP	Input	…
10	R&D Expenditure of the Business Sector	All R&D expenditures in the business sector as percentage of regional GDP	Input	…
11	Non-R&D Innovation Expenditures (SME)	Sum of total innovation (excluding intramural and extramural R&D) expenditure for SMEs as percentage of SMEs' total turnover	Input	…
12	SMEs Collaborating for Innovation	Number of SMEs with innovation co-operation activities (co-operation agreements on innovation activities with other enterprises or institutions) as percentage of total SMEs	Input	…
13	Population with Tertiary Education	Persons aged 30-34 years with some form of post-secondary education as percentage of total population aged 30-34 years	Input	…
14	Lifelong Learning	Persons in private households aged 25-64 years who have participated in the four weeks preceding the interview in any education or training as percentage of total population aged 25-64 years	Input	…
15	Employment in Mid- and High-Tech Manufacturing (MHTM) and Knowledge-Intensive (KIS) Services	Employed persons in medium-high and high-tech manufacturing sectors and in knowledge-intensive services sectors as percentage of total workforce including all manufacturing and service sectors	Input	…
16	Most-Cited Publications	Number of scientific publications among the top-10% most cited publications worldwide as percentage of total scientific publications in the region	Input	Scientific Publications
17	Public-Private Co-Publications	Number of public-private co-authored research publications per million population	Input	
18	International Scientific Co-Publications	Number of scientific publications with at least one co-author based abroad per million population	Input	

Notes: EPO stands for European Patent Office. GDP stands for Gross Domestic Product. PPS stands for Purchasing Power Standard. EUIPO stands for European Union Intellectual Property Office. SME stands for small- and medium-sized enterprises. R&D stands for research and development. Indicators are derived from the RIS 2017 dataset. Sectors considered in the indicator "Exports in Mid- and High-Tech Manufacturing" include "Chemicals and chemical products", "Machinery and equipment", "Office machinery and computers", "Electrical machinery and apparatus", "Radio, television and communication equipment", "Medical, precision and optical instruments", Motor vehicles, trailers and semi-trailers", and "Other transport equipment". Manufacturing sectors considered in the indicator "Employment in Mid- and High-Tech Manufacturing (MHTM) and Knowledge-Intensive (KIS) Services" are "Chemicals", "Machinery", "Office equipment", "Electrical equipment", "Telecommunications and related equipment", "Precision instruments", "Automobiles", and "Aerospace and other transport", while services sectors are "Water transport", "Air transport", "Post and telecommunications", "Financial intermediation", "Insurance and pension funding", "Activities auxiliary to financial intermediation", "Real estate activities", "Renting of machinery and equipment", "Computer and related activities", "Research and development", and "Other business activities". See Hollanders and Es-Sadki (2017) for details.

Table 2. Descriptive statistics of the dependent and explanatory variables.

Variables	Mean	Std. Dev.	Min.	Max.
Dependent Variable				
Innovation Output_r	0.509	0.214	0	1
Innovation Inputs				
Innovation Input_r	0.457	0.178	0	1
Public R&D Expenditure_r	0.480	0.175	0	1
Business R&D Expenditure_r	0.335	0.190	0	1
Non-R&D Innovation Expenditure_r	0.417	0.165	0	1
SMEs Collaborating for Innovation_r	0.331	0.209	0	1
Employment in MHTM and KIS Secors_r	0.419	0.203	0	1
Scientific Publications_r	0.431	0.202	0	1
Human Capital_r	0.408	0.199	0	1
Lifelong Learning_r	0.410	0.218	0	1
Control Variables				
Institutional Quality_r	0.605	0.244	0	1
GDP Per Capita_r	0.355	0.220	0	1
Unemployment Rate_r	0.257	0.214	0	1
Employment Density_r	0.038	0.101	0	1
Population_r	0.201	0.183	0	1

Notes: Statistics refer to a sample of 194 regions.

Table 3. Correlation matrix of the explanatory variables.

Explanatory Variable		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]
Innovation Input$_r$	[1]	1													
Public R&D Expenditure$_r$	[2]	0.64	1												
Business R&D Expenditure$_r$	[3]	0.78	0.37	1											
Non-R&D Innovation Expenditure$_r$	[4]	0.15	0.07	0.10	1										
SMEs Collaborating for Innovation$_r$	[5]	0.66	0.31	0.35	0.02	1									
Employment in MHTM and KIS Secors$_r$	[6]	0.60	0.23	0.69	0.07	0.10	1								
Scientific Publications$_r$	[7]	0.86	0.67	0.59	-0.10	0.59	0.41	1							
Human Capital$_r$	[8]	0.63	0.32	0.33	-0.10	0.38	0.23	0.49	1						
Lifelong Learning$_r$	[9]	0.77	0.39	0.53	-0.12	0.54	0.30	0.69	0.48	1					
Institutional Quality$_r$	[10]	0.70	0.32	0.61	-0.04	0.53	0.33	0.64	0.38	0.75	1				
GDP Per Capita$_r$	[11]	0.80	0.45	0.63	-0.08	0.49	0.53	0.83	0.45	0.70	0.73	1			
Unemployment Rate$_r$	[12]	-0.39	-0.11	-0.51	-0.06	-0.18	-0.57	-0.27	-0.01	-0.27	-0.44	-0.40	1		
Employment Density$_r$	[13]	0.31	0.23	0.12	-0.06	0.22	0.26	0.36	0.31	0.11	0.10	0.42	-0.07	1	
Population$_r$	[14]	0.26	0.09	0.26	-0.05	0.19	0.16	0.21	0.26	0.17	0.01	0.17	-0.04	0.11	1

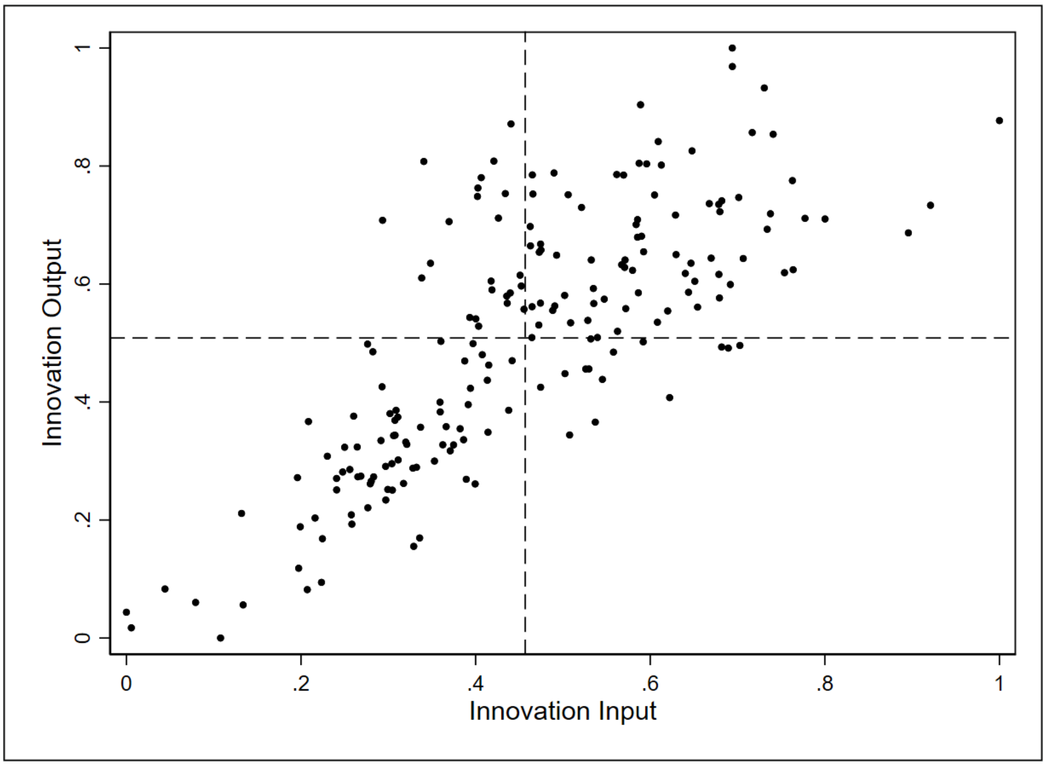
Notes: Correlation coefficients refer to a sample of 194 regions.

Table 4. Average marginal effects of the Heteroskedastic Fractional Probit Models.

Estimation Method	Heteroskedastic Fractional Probit Model				
Dependent Variable	Innovation Output$_r$				
Institutional Quality as Moderating Variable	No	No	No	No	Yes
	(1)	(2)	(3)	(4)	(5)
Innovation Input$_r$	0.958****	0.298****	0.463****	…	…
	(0.042)	(0.062)	(0.069)		
Public R&D Expenditure$_r$	…	…	…	-0.062	-0.001
				(0.053)	(0.039)
Business R&D Expenditure$_r$	…	…	…	0.244***	0.237****
				(0.083)	(0.045)
Non-R&D Innovation Expenditure$_r$	…	…	…	0.210****	0.211****
				(0.048)	(0.030)
SMEs Collaborating for Innovation$_r$	…	…	…	0.184**	0.210**
				(0.078)	(0.089)
Employment in MHTM and KIS Secors$_r$	…	…	…	0.116**	0.179***
				(0.052)	(0.066)
Scientific Publications$_r$	…	…	…	0.106*	0.100**
				(0.059)	(0.049)
Human Capital$_r$	…	…	…	-0.020	-0.081
				(0.068)	(0.057)
Lifelong Learning$_r$	…	…	…	0.086	0.002
				(0.100)	(0.105)
GDP Per Capita$_r$	…	0.304****	-0.145	-0.064	-0.025
		(0.063)	(0.105)	(0.088)	(0.130)
Unemployment Rate$_r$	…	-0.433****	-0.476****	-0.303***	-0.261**
		(0.073)	(0.116)	(0.112)	(0.107)
Employment Density$_r$	…	-0.105	0.226*	0.166	0.035
		(0.166)	(0.127)	(0.128)	(0.104)
Population$_r$	…	0.125*	0.144***	0.109*	0.105****
		(0.068)	(0.053)	(0.064)	(0.021)
Institutional Quality$_r$	…	0.098*	0.167**	0.136	0.092
		(0.055)	(0.067)	(0.085)	(0.057)
Country Dummies	No	No	Yes	Yes	Yes
Number of Regions	194	194	194	194	194
H$_0$: Homoskedastic Variance (χ^2 [p-value])	38.29 [0.000]	84.17 [0.000]	17.69 [0.007]	23.94 [0.032]	117.35 [0.000]
Log Pseudo-Likelihood	-122.24	-118.67	-117.27	-116.67	-116.43
Model Wald χ^2 [p-value]	77.74 [0.000]	38.72 [0.000]	120.48 [0.000]	75.04 [0.000]	83.19 [0.000]
Akaike Information Criterion	250.47	263.34	290.55	317.34	272.86

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; **** $p < 0.001$. Robust standard errors in parentheses. Estimated average marginal effects refer to the HFPMs presented in Table A2 (Online Supplementary Material).

Figure 1. Distribution of regions by relative innovation output and relative innovation inputs endowment.



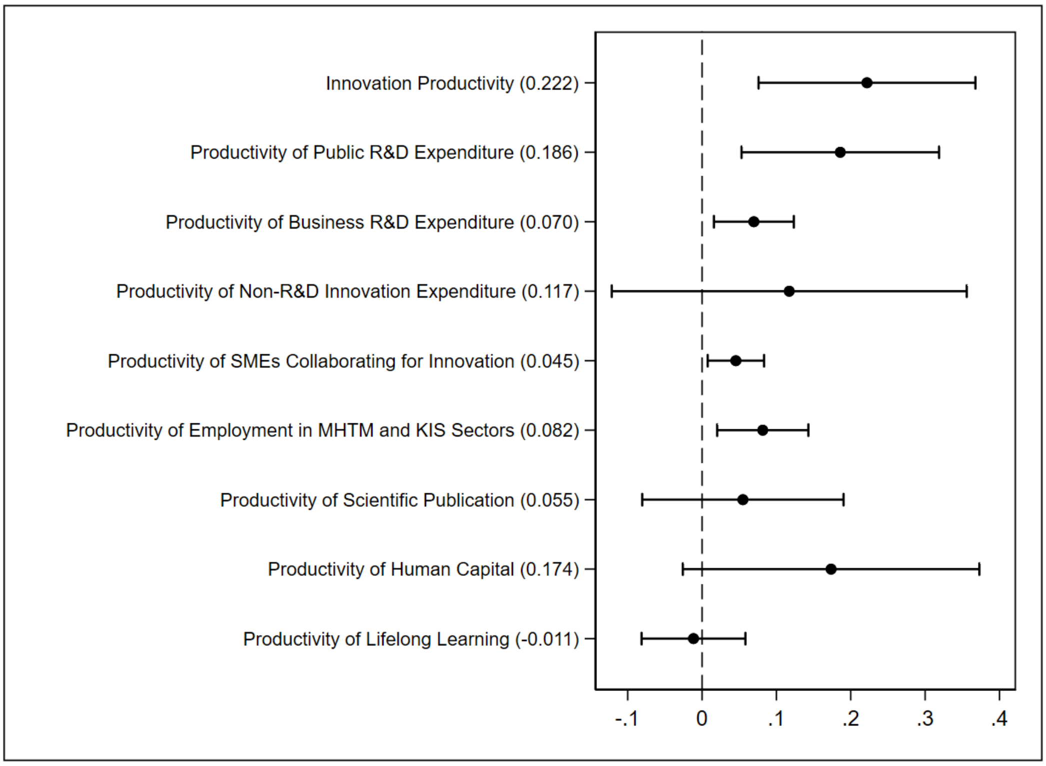
Notes: The plot is defined with respect to the variables for relative innovation performance ($Innovation\ Output_r$) and relative 'overall' innovation capability ($Innovation\ Input_r$). Dashed lines refer to mean values of the two variables. 80 regions (41.2% of the sample) lie in the high-high quadrant; 77 regions (39.7% of the sample) lie in the low-low quadrant; 23 regions (11.9% of the sample) are relatively low-endowed with innovation inputs, but lie above the sample average in terms of innovation performance; 14 regions (7.2% of the sample) are relatively high-endowed with innovation inputs, but lie below the sample average in terms of innovation performance.

Table 5. Marginal effects of innovation inputs and the moderating role of institutional quality.

Dependent Variable	Innovation Output_r				
Moderating Variable	Institutional Quality_r				
Distribution of the Moderating Variable	1st Percentile	25th Percentile	50th Percentile	75th Percentile	99th Percentile
Public R&D $\text{Expenditure}_\text{r}$	-0.319***	-0.076	0.080**	0.180****	0.304****
	(0.107)	(0.073)	(0.039)	(0.030)	(0.078)
Business R&D $\text{Expenditure}_\text{r}$	-0.063	0.053	0.195**	0.315****	0.493****
	(0.122)	(0.076)	(0.077)	(0.095)	(0.137)
Non-R&D Innovation $\text{Expenditure}_\text{r}$	0.378***	0.282****	0.209****	0.155***	0.079
	(0.123)	(0.056)	(0.043)	(0.049)	(0.068)
SMEs Collaborating for $\text{Innovation}_\text{r}$	0.311*	0.273**	0.232**	0.199*	0.146
	(0.170)	(0.134)	(0.103)	(0.108)	(0.181)
Employment in MHTM and KIS Secors_r	0.230**	0.179***	0.158*	0.148	0.138
	(0.100)	(0.067)	(0.082)	(0.102)	(0.135)
Scientific $\text{Publications}_\text{r}$	0.617****	0.402***	0.169**	-0.023	-0.311**
	(0.173)	(0.132)	(0.082)	(0.058)	(0.144)
Human Capital_r	-0.032	-0.115	-0.146	-0.155	-0.154
	(0.091)	(0.073)	(0.093)	(0.099)	(0.108)
Lifelong Learning_r	-0.053	0.031	0.062	0.071	0.071
	(0.275)	(0.162)	(0.113)	(0.149)	(0.261)

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; **** $p < 0.001$. Robust standard errors in parentheses. The table reports the estimated marginal effects of the individual innovation inputs at different percentiles of the institutional quality variable. Estimated marginal effects refer to specification (5) in Table 4, and specification (5) in Table A2 (Online Supplementary Material).

Figure 2. Innovation productivity and institutional quality – Average marginal effects.



Notes: The plot reports the estimated average marginal effect (along with confidence intervals) of institutional quality on separated dependent variables capturing innovation productivity. The estimated average marginal effect is shown in parentheses besides the name of each dependent variable. Average marginal effects and statistics referring to the estimated HFPMs are reported in Table A9 (Online Supplementary Material).