UNIVERSIDADE CATÓLICA PORTUGUESA

REGIONAL INNOVATION HETEROGENEITY IN EUROPE

A Quantile Regression Analysis

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Manuel António Marques Antunes

under the orientation of

Professor Doutor Carlos Manuel Ferreira dos Santos

Universidade Católica Portuguesa, Católica Porto Business School
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Resumo

O propósito desta tese é o de analisar a existência de heterogeneidade a nível regional em termos de comportamento de inovação entre Regiões Europeias. Foram estimados regressões de quantis com uma variável dependente discreta, uma avançada ferramenta econométrica indicada para analises empíricas evolucionistas, o que representa uma novidade na área de inovação regional. Aplicando quantis a uma contagem de amostra de 67 regiões Europeias, e usando quarto quantis, concluímos uma evidência de heterogeneidade. A heterogeneidade existe em termos de performance de inovação regional e entre os fatores influenciadores dessa performance e em todos os níveis de performance considerados. Esta análise permite obter conclusões de grande relevância a serem consideradas na Europa 2020.

Palavras-chave: Inovação Regional, I&D, Patentes, Regressão de Quantis, Quantis para dados de contagem, Heterogeneidade

Abstract

The aim of this paper is to analyse the existence of regional heterogeneity in terms of innovation behaviour, between European Regions. We have estimated quantile regressions with a discrete dependent variable, an advanced econometric tool indicated for empirical evolutionist analysis, which is a novelty in the area of regional innovation. Applying quantile for counts within a sample of 67 European regions, and using four quantiles, we have concluded for the evidence of heterogeneity. The heterogeneity exists in terms of regional innovation performance and also within the factors influencing that performance, in each level of performance considered. This analysis allows obtaining conclusions of much relevance to be considered to Europe 2020.

Keywords: Regional Innovation, R&D, Patents, Quantile Regression, Quantile for Counts, Heterogeneity

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Introduction

Regional innovation is presented in the literature as one of the most important explanatory factors for regional development and also for the differences found between regions' development and growth levels.

At this paper, we analyse precisely the explicative variables of regional innovation performance and the existence of regional heterogeneity through those variables, depending on the level of innovation performance from the considered regions.

Usually, the empirical applications in this field, particularly, in the evolucionist analysis of regional innovation, use one of the methodologies proposed by Cantner and Krüger (2007): non parametric analysis of productive efficiency, in particular, the Data Envelopment Analysis.

We intend to improve the measurement of European regional innovation heterogeneity, making a novel appliance of quantile regression to this field.

In the literature, there are many recent studies about regional innovation (e.g. Antonenko (2014), Buerger et al. (2012), Doh and Kim (2014), Vieira et al. (2008), Esen and Asik-Dizdar (2014), Fragkandreas (2013), Sleuwaegen and Boiardi (2014)). Also, it is possible to find some studies about innovation heterogeneity (for example, Capello and Lenzi, 2014) and about regional innovation heterogeneity (for example, Guastella and van Oort, 2015). Concerning the use of quantile regressions, Crespo-Cuaresma et al. (2011) analyse the regional economic growth with this methodology. Differently, but using the same methodology, Ebersberger and Herstad (2013) study the relation between international innovation collaboration, intramural R&D and SMEs' innovation performance, and Ebersberger et al. (2010) try to understand the relation between R&D and innovation.

Notwithstanding, there are not studies like this one, where we try no analyse regional innovation heterogeneity with quantiles for counts.

In fact, with this study, we want to know if regional innovation in Europe can be quantified or, at least, quantitatively demonstrated. And if so, we want to figure out if it is possible to identify common factors between regions from the same level of innovation performance, which differ between levels.

We believe the heterogeneity issue is very important for the definition of European policy about innovation, namely within the Europe 2020 projects.

The paper is organized as follows. Chapter 1 and 2 makes a brief revision of the literature about heterogeneity and measurement of innovation respectively. In chapter 3 is presented the methodology we have chosen for in the empirical analysis, and also the data we have used. Chapter 4 presents the reached empirical results and discussion of those results. Finally, there is a Conclusion of the thesis.

Chapter 1
Heterogeneity

Economic behaviour's heterogeneity is a key element in evolutionist economic theories (Cantner and Hanusch, 2001). Moreover, there is an intense debate about the way heterogeneity frames the nature and the structure of the economic system in a certain moment, as well as the way it constricts that system evolution´s structural dynamics.

Heterogeneity refers to the levels of difference between the individuals of a population: families, firms, sectors, countries, or, in what matters for this paper, regions. It is possible to discuss those differences concerning many vectors, but we intend to analyse the level of direction and intensity of innovation activity. On the one hand, agents' heterogeneity is the result of technological change, namely, different activities of innovation, imitation and adaptation. On the other hand, it is a decisive element of that technological change: makes pressure on the delayed agents to copy and to imitate, and also makes pressure on the advanced agents to continue the leadership of the innovation process. Additionally, heterogeneity propitiates different learning processes which induce different performances.

Conceptually, this notion is close from the one of variety or diversity presented by Saviotti (1996, 1998a, 1998b). These terms refer to the economic system composition's change. Variety is the set of actors, activities or objects which are necessary to characterize the economic system (Saviotti, 2001). It is simultaneously a requirement to economic development and complementary to that development.

So, heterogeneity and variety are close, but are not the same. There are relevant differences, both generically and specifically, when applied to the innovation process. Heterogeneity covers, beyond the variety of outputs, differences of quality and of progression of the scale of products' attributes (Lancaster, 1966). In terms of inputs, beyond the variety, heterogeneity also covers differences about efficiency and requirements.

From the investigation program of the Augsburg School, in the nineties, has resulted a conceptual approach about the relation between heterogeneity and innovation. This approach has its roots on the pioneer work of Dosi (1988), for whom variety is a particular case of asymmetry. In short, heterogeneity can be understood as different innovations' successes, accumulated until a certain moment by an entity, for example, a region.

Chapter 2
Innovation

Innovation takes an important role in the economy, Torben Schubert & Léopold Simar (2010), divide this role in two ways, macro and microeconomic, at a macroeconomic level they consider it as a driver of technological progress and as a microeconomic as a driver of firm competitive advantage.

To study and defining the indicators of innovation its first necessary to understand what is the concept of innovation. Innovation is understood as the process of transformation of productive resources in desirable goods by the consumer that represents novelty at acceptable prices, meaning the creation of something qualitatively new through learning and knowledge (The Oxford Handbook of Innovation, Measuring Innovation). It involves the competencies change and the capacity to produce something new that takes to performance increase.

There exists some conditions that are propitious to the innovative process as the capacity to obtain higher quality resources at lower prices, the relations between innovative agents and the government and its own society and the culture that it's located. This provides us many possibilities of variables that can be used as indicators in the characterization of innovative capacity, in the sense that the innovation characteristics do not exclude the possibility of its measurement (Smith, 2005).

There isn't howsoever an indicator that sustained all the characteristics of innovation, which makes its measure imperfect, there is also some kind of innovation that have no possible way of measurement, this brings some acknowledge difficulties to its indicators. Smith (2005) suggests three dimensions of the innovation measurement's difficulties: to define what is new; to define rigorously the way of measurement; and to understand that the reality studied can be measured in different ways.

The most common indicators used to measure innovation by The Oxford Handbook of Innovation are Research and Development (R&D), Data on Patent Application and Bibliometric Data (data on scientific publication and citation), however this last one is excluded by the fact that this data is more applicable to information about used technics and science and not to innovation itself. So we assumed R6D and data on patent application as the used indicators to measure innovation.

2.1. Innovation Indicators – R&D

In the case of R&D, this is a very controversy indicator because this expenditures are only considered an innovation input (Kleinknecht et al. 2002), and opposite of what was defended by Rosenberg (1976, 1982), Fagerberg (2005) and Bell & Pavitt (1993), innovation it's not deterministic and sequential as Laestadius (2003) state: it's used as an indicator taking in mind the idea that scientific investigation precedes the innovation

However, there exists some other advantages in the use of R&D as an indicator like the fact that it's a long period indicator, the meticulous sub classifications of some countries and the good harmonization across countries (The Oxford Handbook of Innovation, Measuring Innovation).

2.2. Innovation Indicators – Data on Patent Applications

Relatively to patent data, by being a public contract between an inventor and government it guarantees to the inventor a monopoly, with limited time, of use of its invention (Iversen, 1998, The Oxford Handbook of Innovation, Measuring Innovation). It's considered a good indicator and its use has been increasing during past years because of the increased number of invention and as a result of a strategy used by companies, another strong point it's the easy and free access of it.

Through Smith (2005) it's possible to appoint some vantages to the use of patent data, like the fact of those only be attributed to inventions with commercial purpose that it translates in innovation; keeps technical information about innovations; and allows obtaining many as sectional and temporal data.

It's also possible in the meantime point out some disadvantages (Kleinknecht et al. 2002 in The Oxford Handbook of Innovation, Measuring Innovation) as the fact of sometimes, some innovations disregard the patent process or the patent is not applicable to in its case so they are missed in this measure of innovation. It can also be an indicator non homogeneous among the different countries.

Notwithstanding, we believe the number of registered patents is still a good indicator. Not also due to its availability, but because it is an output indicator. So, if we want to analyse the innovation performance it will be better to use this kind of indicator, although it is not perfect. That is the reason why we will use this measure of innovation in this paper.

Chapter 3
Methodology and Data

Quantile regression is considered an econometric tool with a very high potential to be used in the field of evolumetrics (Cantner and Krüger, 2007), as it is in many other economic areas. Evolumetrics is a set of econometric and operations research tools, very well adapted to characterize heterogeneous realities and contexts with a structural evolution. In fact, to make an empirical evolutionist analysis, given the independent variables, a statistical tool that allows the characterization of the dependent variable´s total distribution is needed. Just using this, it is possible to empirically describe the heterogeneity of the technological structures, development levels and innovation capabilities.

Quantile regressions were introduced by Koenker and Bassett (1978), who suggested the estimation of conditional quantile functions, as an alternative to the conditional expected values, which have been used by the traditional econometrics until then. Following the authors, the conditional quantile function of order τ could be found through:

$$\min_{\beta \in \Re} \sum_{i=1}^{N} \rho_\tau \left(y_i - \xi(\mathbf{x}_i \boldsymbol{\beta}) \right)$$

where y_i is the dependent variable, $\mathbf{x}_i$ is the line vector which includes k independent variables relevant to the understanding of the phenomenon in analysis, $\boldsymbol{\beta}$ is the column vector of k regression coefficients, τ is the order of the quantile, ξ is the median of the population and ρ is the disturbed module function.

3.1. Model

Usually, when the dependent variable is the region´s capability to innovate, the measure used is the number of patents of each region. This is a count variable, which is more defying in terms of econometrics. In fact, discrete dependent variable models, as well as count dependent variable models need special estimation and statistical analysis methodologies.

In this paper, we estimate a conditional quantile function when the dependent variable is a count variable (quantiles for counts).

The popularity of the quantile regression has led to the appearance of many investigation lines, changing the dependent variable. Manski (1985) and Horowitz (1992) considered binary dependent variable end the multinomial models; Powell (1984, 1986) studied the censored/truncated dependent variable; Lee (1992) analysed ordered discrete choice models (eg. ordered probit models); Koenker and Geling (2001) and Koenker and Bilias (2001) used quantile regression in duration problems.

The extension of quantile regression to count models is based in the seminal work of Hausman et al. (1984) and Gourieroux et al. (1984) about count models. However, this extension arises important technical difficulties. The most important is related with the simultaneous existence of a not differentiable objective function and a discrete dependent variable. This problem prevents the use of traditional techniques, based in Taylor series expansions, to obtain the asymptotic distribution of the parameters estimators of the conditional quantile functions.

Machado and Silva (2005) suggested a consensual solution to this problem: an artificial flatting of the data, based in a specific form of jittering introduced by Stevens (1950) in another context. The goal is to build a continuous variable, whose conditional quantiles have a univocal relation with the conditional quantiles of the count discrete variable. The artificial variable will be the base for the statistical inference.

In this paper, we use the methodology proposed by Machado and Silva (2005) for the estimation of conditional quantile function when the dependent variable is a count variable. In particular, we have used the software Stata 9.2 with the package Qcount developed by Miranda (2007) based on the Machado and Silva (2005)'s methodology

3.2. Data

The dependent variable of our model is the number of high-tech patents (destined to high technology industries) in European regions (y), and the independent variables are the following ones:

- Percentage of the regional population, between 25 and 64 years old, with superior education (x1);
- Percentage of the regional population, between 25 and 64 years old, who participate in lifelong learning (x2);
- Percentage of the regional working force employed in high-tech level services (x3);
- Percentage of the regional working force employed in medium-high and high-tech level industries (x4);
- Public expenditure in Research and Development (R&D) as percentage of regional Gross Domestic Product (GDP) (x5);
- Private expenditure in R&D as percentage of regional GDP (x6);
- Regional GDP per capita (x7).

The data related with y, x1, x2, x5 and x6 was obtained from the European Innovation Scoreboard (2002); x3, x4 and x7 are from Eurostat (1998).

The sample covers 67 European regions (listed in Appendix), for which it was possible to get all this information. The regions analysed are from Germany, Finland, Holland, Spain, Italy, Portugal and France.

Chapter 4
Empirical results and Discussion

Table 1 presents a summary of descriptive statistics related with the independent variables used in our model.

Table 1 Descriptive Statistics

	x1	x2	x3	x4	x5	x6	x7
Mean	20,03	6,02	3,05	7,2	0,66	0,86	19323
Standard Deviation	7,12	4,63	1,24	3,3	0,44	0,59	5244
Asymmetry	0,1	1,66	1,01	0,89	1,36	1,04	1,12
Excess kurtosis	-0,78	1,45	0,65	0,7	1,68	1,03	2,98
Minimum	7,34	1,84	0,74	2,14	0,08	0,1	8738
Maximum	33,6	18,9	6,49	18,3	2,08	2,9	40267

The observed statistics for the percentage of the regional population, between 25 and 64 years old, with superior education (x1), show some differences between the regions, in spite of the existence of asymmetry and excess kurtosis coefficients that are not enough to reject the null hypothesis of normal distribution of the variable, as p-value is 0,4189 (using a Hansen-Doornik (1994) test). In fact, there are clear differences between the maximum and the minimum, as well as between the mean and the standard deviation (the coefficient of variation is 36%, indicating a standard deviation clearly inferior to the mean).

Concerning the lifelong learning (x2), the reality is quite different. This variable shows very sharp regional differentiation levels: the excess kurtosis coefficient is almost the double of the previous one, the coefficient of variation is 78% of the mean, and the normality test leads to the rejection of the null hypothesis (p-value is almost 0). We can conclude that the European regional behaviour is substantially different depending on considering formal or lifelong education. From the region´s capability to innovate point of view, this is an important difference, as innovation demands the existence of a permanently updated working force, capable of inducing and assimilating the new technologies. Naturally, the analysis of our econometric model will allow us to understand the relative importance of these factors.

The other variables characterized in table 1 show some behavioural similarity, with the exception of regional GDP per capita (x7), which exhibits an excess kurtosis coefficient and a standard deviation clearly high. However, all the variables show enough sample heterogeneity for the rejection of a normality test, indicating the existence of differences between the regions considered, in each of the analysis dimensions, which justifies entirely the regression analysis.

The descriptive statistics analysis will be more complete with the presentation of the correlations matrix between the variables of the model (table 2). Naturally, the linear correlation does not capture all the dynamics associated to the innovation process, and that is why we will make a heterogeneity characterization based on the analysis of different quantiles.

Table 2 Correlations Matrix

	y	x1	x2	x3	x4	x5	x6	x7
y	1	0,43	0,17	0,4	0,34	0,26	0,72	0,57
x1		1	0,32	0,39	-0,1	0,46	0,44	0,31
x2			1	0,39	-0,33	0,43	0,04	0,18
x3				1	-0,15	0,65	0,38	0,48
x4					1	-0,3	0,55	0,34
x5						1	0,22	0,21
x6							1	0,59
x7								1

Table 2 allows standing out some particular facts. Firstly, the number of high-tech patents (y) exhibits one low correlation with public expenditure in R&D (x5), but a high correlation with the private one (x6). Clearly, private R&D aims at finding market power and obtaining profit, therefore there will be patents registrations.

Concerning education (formal or lifelong), there are some paradoxes which deserve to be underlined. In particular, the negative correlation between both types of education (x1 and x2) and the working force employed in medium-high and high-tech level industries (x4). This result could be just a consequence of this kind of measure, but we will try to clarify this situation through the quantile regressions.

Another relevant result is the high correlation between public expenditure in R&D (x5) and the percentage of the regional working force employed in high-tech level services (x3), contrasting with a low correlation between this type of working force and private expenditure in R&D (x6). Probably, public expenditure is more likely to providing services to support innovation. This conclusion corroborates the first one described above, and is also validated by the negative correlation between the two types of working forces. The negative correlation between public expenditure in R&D and the percentage of the working force employed in medium-high and high-tech level industries could be seen as another facet of this reality.

It is important to point out that following this matrix we cannot conclude for the existence of a crowding-out between private and public expenditure in R&D, but it seems to exist a crowding-out related to the type of job creation in R&D.

For the econometric estimation of count data quantile regressions, we have considered the quantiles of order 10%, 25%, 50% and 90% of the conditional distribution of the number of high-tech patents in the European regions of our sample. The quantile of order 10% corresponds to those regions with a very low revealed capacity of innovation, while the 90% quantile covers those regions with a very high innovative ability. The choice of these quantiles has the purpose of capturing enough cuts in the distribution to check the existence of heterogeneity, evaluating which explanatory factors, with statistical relevance/significance, differ according the quantiles.

4.1. At a 10% Quantile

Table 3 Estimation Results for quantile 10%

	Coef.	Std. Err.	z	P>z
x1	0,0413247	0,0391003	1,06	0,291
x2	0,0406873	0,0346807	1,17	0,241
x3	0,1828581	0,1127165	1,62	0,105
x4	0,072751	0,037066	1,96	0,050
x5	0,3014826	0,3351198	0,90	0,368
x6	0,5047431	0,2908115	1,74	0,083
x7	0,0000413	0,0000208	1,99	0,047
constant	-2,329217	0,7033813	-3,31	0,001

Table 3 illustrates the estimation results for quantile 10%. Analysing the p-values of each variable, and assuming a significance level of 5%, we can conclude that only the regional GDP per capita (x7), and marginally the percentage of the regional working force employed in medium-high and high-tech level industries (x4), are statistically significant. If we allow a significance level of 10%, the private expenditure in R&D (x6) is also significant.

The regions in this quantile have a very low innovation capability. Thus, innovation will tend to assume the form of technologies that do not demand special qualifications, which is probably the reason why educational variables (x1 and x2) are nor significant. Also, innovation will not request specialized services support, so it was expectable the not rejection of the null hypothesis of absence of individual significance of the percentage of the regional working force employed in high-tech level services (x3). The absence of significance of public investment shows that innovation is not a priority for the regional growth policy.

Analysing the not conditional distribution, the regions in this quantile are Portuguese (Norte and Lisboa e Vale do Tejo), Spanish (Andalucia, Asturias, and Pais Vasco) and Italian (Campania and Puglia).

There are some general characteristics of these regions that can be useful to understand their presence in this quantile. Generally, these regions have an unfavourable production specialization. Following Pavitt (1984) taxonomy, there is a specialization in activities dominated by suppliers, with low capacity of technological accumulation internal to firms. Moreover, working force qualifications are, usually, at a low level, and production has a low added value (Oliveira, 2011).

4.2. At a 25% Quantile

Table 4 Estimation Results for quantile 25%

	Coef.	**Std. Err.**	**z**	**P>z**
x1	0,044526	0,0195876	2,27	0,023
x2	0,0317638	0,0253658	1,25	0,210
x3	0,1133976	0,1388473	0,82	0,414
x4	0,1008021	0,0699224	1,44	0,149
x5	0,4444755	0,3203632	1,39	0,165
x6	0,2700574	0,4825653	0,56	0,576
x7	0,0000714	0,0000413	1,73	0,084
constant	-2,583199	0,6195864	-4,17	0,000

Table 4 reports the estimation output concerning the conditional quantile function when $\tau = 0{,}25$. Using a significance level of 5%, we can say the variable related with the percentage of the regional population, between 25 and 64 years old, with superior education (x1) is the only one for which it would be rejected the null hypothesis in an individual significance test. With a 10% level of significance, the regional GDP per capita (x7) is also significant. Additionally, the estimated effect's signal of both variables over the number of patents is positive, as was expected.

In this quantile, the innovation capacity is bigger than in the previous one, as such it is understandable that knowledge in terms of tertiary education became significant.

The first two conditional quantile functions allow concluding that there are statistically relevant variables in the first decile, which are not for the first quartile. This shows regional technological heterogeneity: regional innovation ability depends on different factors, according the conditional function´s quantile where regions are.

The additional regions when we consider the not conditional distribution of quantile 25%, include four Spanish regions (Castilla y Léon, Islas Baleares, Galicia and Comunidad Valenciana), two Italian regions (Liguria and Umbria) and three French regions (Bourgogne, Champagne-Ardenne and Limousin).

According to Pavitt (1984) taxonomy, the most important sectors in these regions are dominated by suppliers and production based (Oliveira, 2011). In fact, there are not many technological opportunities in this specialization profile. It is possible to say that there is a lock in in unfavourable trajectories (Oliveira, 2011), which prevents or makes more difficult the innovation performance.

4.3. At a 50% Quantile

Table 5 Estimation Results for quantile 50%

	Coef.	Std. Err.	z	P>z
x_1	0,0441831	0,0218219	2,02	0,043
x_2	0,039008	0,0251633	1,55	0,121
x_3	0,0644671	0,1472504	0,44	0,662
x_4	0,1130385	0,0494783	2,28	0,022
x_5	0,4774073	0,4801216	0,99	0,320
x_6	0,2977382	0,3026345	0,98	0,325
x_7	0,0000787	0,0000446	1,76	0,078
constant	-2,545198	0,6835084	-3,72	0,000

Furthermore, table 5 shows the estimation results when we consider the quantile 50%. In this scenario, the significant variables to a 10% significance level are not substantively different from the ones in the previous quantile. In fact, the regional GDP per capita (x7) and the percentage of the regional population, between 25 and 64 years old, with superior education (x1) are statistically relevant in both cases.

However, there is an important difference between the two quantiles, which helps to express and characterize the heterogeneity in European regions' technological structures. Actually, the percentage of the regional working force employed in medium-high and high-tech level industries (x4) is statistically significant, even at 2,5% significance level.

At this quantile, we find many French regions (Auvergne, Languedoc-Roussilon, Nord-Pas-de-Calais, Midi-Pyrénées, and others), also many Italian (Abruzzo, Friuli-Venezia Giulia, and others), and even some German (Sachsen-Anhalt, Thüringen and Sachsen) and some Dutch regions (Flevoland and Zeeland).

Probably, these regions are at this intermediate quantile because their innovation dynamics it is not yet of a high level. In fact, their R&D expenditures are below the average, when we compare with others from the same country (Oliveira, 2011)

4.4. At a 90% Quantile

Table 6 Estimation Results for quantile 90%

	Coef.	**Std. Err.**	**z**	**P>z**
x1	0,0628783	0,0159098	3,95	0,000
x2	0,0217423	0,0511281	0,43	0,671
x3	0,202909	0,1154608	1,84	0,057
x4	0,1216851	0,0323385	3,76	0,000
x5	-0,180678	0,5293183	-0,34	0,733
x6	0,6426493	0,3225496	1,99	0,046
x7	0,000062	0,0000348	1,78	0,075
constant	-2,170818	1,009818	-2,15	0,032

Finally, table 6 presents the estimation results regarding the conditional quantile function for quantile 90%. There are extremely interesting conclusions at this quantile.

Firstly, with a 5% significance level, the relevant variables are the ones related with the private expenditure in R&D as percentage of regional GDP (x6), the percentage of the regional population, between 25 and 64 years old, with superior education (x1) and the percentage of the regional working force employed in medium-high and high-tech level industries (x4). But if we allow (as we have done before) an higher significance level, in particular 10%, we also have as significant variables the regional GDP per capita (x7) and the percentage of the regional working force employed in high-tech level services (x3).

Again, there is statistical evidence supporting the existence of technological heterogeneity in European regions. The factors that affect the innovation performance are actually different, depending on the conditional distribution quantile where the region is.

We find at this quantile several regions, which were expectable to be found here. In fact, we find French regions (Île de France, Rhône-Alpes), German regions (Baden-Württemberg, Bayern, Hessen) and Finnish regions (Etelä-Suomi, for example).

The industrialization profile of these regions is much diversified. Furthermore, high technology industries show a significant growth, and there are many technological centers and many university liaisons (Oliveira, 2011). According to Pavitt (1984), the predominant sectors are the ones of information and science based. Usually, these sectors are associated to the enhancement of innovation performance.

Conclusion

The empirical analysis we have conducted at this paper allow us to conclude for the evidence of heterogeneity, concerning regional innovation in Europe.

In fact, quantile regression allowed the identification of the innovation´s determinant factors, in regions with low and high innovation capacity. Depending on the level of innovation performance, the explanatory factors of that level are different.

Therefore, we can demonstrate in a quantitative way that it is an error to blindly import models of regional innovation policies, because the reality of European regions is heterogeneous. If in different stages of innovation competence, there are different variables exhibiting statistical significance, it is possible to say that political instruments should be different and should focus on different variables, according the region typology in discussion.

Naturally, in the future, it would be of great importance to improve the innovation indicator and to widen the sample to a bigger number of regions.

References

Antonenko, I. (2014). "Innovation Development Sectoral Trajectories of the South Russian Regions", *Regional and Sectoral Economic Studies*, vol. 14(2), pp. 31-38.

Bell, M. and Pavitt, K. (1993). "Technological Accumulation and Industrial Growth: contrasts between developed and developing countries", *Industrial and Corporate Change*, vol. 2(2), pp. 157-210.

Buerger, M., Broekel, T. and Coad, A. (2012). "Regional Dynamics of Innovation: Investigating the Co-evolution of Patents, Research and Development (R&D), and Employment", *Regional Studies*, vol. 46(5), pp. 565-582.

Cantner, U. and Hanusch, H. (2001). "Heterogeneity and Evolutionary Dynamics – Empirical Conception, Findings and Unresolved Issues", in *Frontiers of Evolutionary Economics – Competition, Self-Organization and Innovation Policy*, J. Foster and J.S. Metcalfe (coord.), pp. 228-277, Northhampton: Edward Elgar Publishing.

Cantner, U. and Krüger, J.J. (2007). "Empirical Tools for the Analysis of Technological Heterogeneity and Change: Some Basic Building Blocks of 'Evolumetrics'", in *Elgar Companion to Neo-Schumpeterian Economics*, chapter 30, Edward Elgar.

Capello, R. and Lenzi, C. (2014). "Spatial Heterogeneity in Knowledge, Innovation, and Economic Growth Nexus: Conceptual Reflections and Empirical Evidence", *Journal of Regional Science*, vol. 54(2), pp. 186-214.

Chen, K., & Guan, J. (2012). "Measuring the Efficiency of China's Regional Innovation Systems: Application of Network Data Envelopment Analysis (DEA)", *Regional Studies*, *46* (January 2015), 355–377.

Crespo-Cuaresma, J., Foster, N. and Stehrer, R. (2011). "Determinants of Regional Economic Growth by Quantile", *Regional Studies*, vol. 45(6), pp. 809-826.

Doh, S. and Kim, B. (2014). "Government support for SME innovations in the regional industries: The case of government financial support program in South Korea", *Research Policy*, vol. 43, pp. 1557-1569.

Dosi, G. (1988). "Sources, Procedures and Microeconomic Effects of Innovation", *Journal of Economic Literature*, vol. 26, pp. 1120-1271.

Ebersberger, B. and Herstad, S.J. (2013). "The relationship between international innovation collaboration, intramural R&D and SMEs' innovation performance: a quantile regression approach", *Applied Economics Letters*, vol. 20, pp. 626-630.

Ebersberger, B., Marsili, O., Reichstein, T. and Salter, A. (2010). "Into thin air: using a quantile regression approach to explore the relationship between R&D and innovation", *International Review of Applied Economics*, vol. 24(1), pp. 95-102.

Esen, A. and Asik-Dizdar, O. (2014). "Regional Innovation as part of Regional Development Agenda in Turkey: The Role of Development Agencies", *Regional and Sectoral Economic Studies*, vol. 14(1), pp. 145-158.

European Innovation Scoreboard (2002). European Innovation Scoreboard 2002, Technical Report N.º 3, European Commission.

Eurostat (1998) (2000), Research and Development Annual Statistics 1999-2000, Office for Official Publications of the European Communities 2001.

Fagerberg, J. (2005). "Innovation: a guide to the literature", in *The Oxford Handbook of Innovation*, J. Fagerberg, D.C. Mowery and R. Nelson (coord.), pp. 1-26, New York: Oxford University Press.

Fagerberg, J., Fosaas, M., & Sapprasert, K. (2012). “Innovation: Exploring the knowledge base”, Research Policy, 41(7), 1132–1153.

Fragkandreas, T. (2013). “When Innovation Does Not Pay Off: Introducing the ‘European Regional Paradox’”, *European Planning Studies*, vol. 21(12), pp. 2078-2086,

Fritsch, M., & Slavtchev, V. (2011). “Determinants of the Efficiency of Regional Innovation Systems”, *Regional Studies*, *45*(7), 905–918

Gourieroux, C., Monfort, A. and Trognon, A. (1984). “Pseudo Maximum Likelihood Methods: Applications to Poisson Models”, *Econometrica*, vol. 52, pp. 701-720.

Guastella, G. and van Oort, F.G. (2015). “Regional Heterogeneity and Interregional Research Spillovers in European Innovation: Modelling and Policy Implications”, *Regional Studies*, vol. 11, pp. 1772-1787.

Hausman, J., Hall, B.H. and Griliches, Z. (1984). “Econometric Models for Count Data with an Application to the Patents-R&D Relationship”, *Econometrica*, vol. 52, pp. 909-938.

Horowitz, J.L. (1992). “A Smooth Maximum Score Estimator for the Binary Response Model”, *Econometrica*, vol. 60, pp. 505-531.

Kleinknecht, A., Van Montfort, K. and Brouwer, E. (2002). “The Non-Trivial Choice Between Innovation Indicators”, *Economics of Innovation and New Technology*, vol. 11(2), pp.109-121.

Koenker, R. and Bassett, G. (1978), “Regression Quantiles”, *Econometrica*, vol. 46(1), pp. 33-50.

Koenker, R. and Bilias, Y. (2001). “Quantile Regression for Duration Data: a reappraisal of the Pennsylvania Reemployment Bonus Experiments”, *Empirical Economics*, vol. 26(1), pp. 199-220.

Koenker, R. and Geling, O. (2001). "Reappraising Medfly Longevity: A Quantile Regression Survival Analysis", *Journal of the American Statistical Association*, vol. 96, pp. 458-468.

Laestadius, S. (2003). "Measuring Innovation in the Knowledge Economy", Pavitt Conference of Innovation, 13 November, SPRU, Sussex.

Lee, M.-J. (1992). "Median Regression for Ordered Discrete Response", *Journal of Econometrics*, vol. 51, pp. 59-77.

Machado, J.A.S. and Silva, J.M.C.S. (2005). "Quantiles for Counts", *Journal of the American Statistical Association*, vol. 100, pp. 1226-1237.

Manski, C.F. (1985). "Semiparametric Analysis of Discrete Response: Asymptotic Properties of the Maximum Score Estimator", *Journal of Econometrics*, vol. 27, pp. 313-333.

Milana, C., Nascia, L., & Zeli, A. (2013). "Decomposing multifactor productivity in Italy from 1998 to 2004: evidence from large firms and SMEs using DEA", *Journal of Productivity Analysis*, *40*(1), 99–109

Miranda, A. (2007). "QCOUNT: Stata Programe to fit Quantile Regression Models for Count Data", Statistical Software Components S456714, Boston College, Department of Economics.

Oliveira, M.A. (2011). *Território e Inovação: Uma aplicação às Regiões Europeias*, Tese de Doutoramento, Faculdade de Economia da Universidade de Coimbra.

Pavitt, K. (1984). "Sectoral patterns of technical change: towards a taxonomy and a theory", *Research Policy*, vol. 13, pp. 343-373.

Powell, J.L. (1984). "Least Absolute Deviation Estimation for the Censored Regression Model", *Journal of Econometrics*, vol. 25, pp. 303-325.

Powell, J.L. (1986). "Censored Regression Quantiles", *Journal of Econometrics*, vol. 32, pp. 143-155.

Rosenberg, N. (1976). *Perspectives on Technology*, Cambridge: Cambridge University Press.

Rosenberg, N. (1982). *Inside the Black Box: Technology and Economics*, Cambridge: Cambridge University Press.

Saviotti, P.P. (1996). *Technological Evolution, Variety and the Economy*, Cheltenham: Elgar.

Saviotti, P.P. (1998a). "Variety, Growth and Demand", Conference of the International Schumpeter Society, 12-14 June, Viena.

Saviotti, P.P. (1998b). "Technological Evolution and Firm Behaviour", in *Advances in Self-organization and Evolutionary Economics*, J. Lesbourne and A. Orléan (coord.), Paris: Economica.

Saviotti, P.P. (2001). "Considerations about a Production System with Qualitative Change", in *Frontiers of Evolutionary Economics. Competition, Self-Organization and Innovation Policy*, J. Foster and J.S. Metcalfe (coord.), pp. 197-227, Northhampton: Edward Elgar Publishing.

Schubert, T., & Simar, L. (2011). "Innovation and export activities in the German mechanical engineering sector: An application of testing restrictions in production analysis", *Journal of Productivity Analysis*, *36*(1), 55–69.

Simar, L., & Wilson, P. W. (1998). Sensitivity Analysis of Efficiency Scores: How to Bootstrap in Nonparametric Frontier Models. *Management Science*, *44*(1), 49–61

Sleuwaegen, L. and Boiardi, P. (2014). "Creativity and regional innovation: Evidence from EU regions", *Research Policy*, 43, pp. 1508-1522.

Smith, K. (2005). "Measuring Innovation", in *The Oxford Handbook of Innovation*, J. Fagerberg, D.C. Mowery and R. Nelson (coord.), pp. 148-177, New York: Oxford University Press.

Stevens, W.L. (1950). “Fiducial Limits of the Parameter of a Discontinuous Distribution”, Biometrika, vol. 37, pp. 117-129.

Vieira, E., Vasquez-Rozas, E. and Neira, I. (2008). “The Innovation Factor: an Econometric Model of Productivity in European Regions”, *Regional and Sectoral Economic Studies*, vol. 8(1), pp. 59-70.

Appendix

DE1	Baden-Württemberg
DE2	Bayern
DE3	Berlin
DE4	Brandenburg
DE5	Bremen
DE6	Hamburg
DE7	Hessen
DE8	Mecklenburg-Vorpommern
DE9	Niedersachsen
DEA	Nordrhein-Westfalen
DEB	Rheinland-Pfalz
DEC	Saarland
DED	Sachsen
DEE	Sachsen-Anhalt
DEF	Schleswig-Holstein
DEG	Thüringen
ES11	Galicia
ES12	Principado de Asturias
ES21	Pais Vasco
ES22	Comunidad Foral de Navarra
ES3	Comunidad de Madrid
ES41	Castilla y León
ES51	Cataluña
ES52	Comunidad Valenciana

ES53	Illes Balears
ES61	Andalucia
FR1	Île de France
FR21	Champagne-Ardenne
FR22	Picardie
FR23	Haute-Normandie
FR24	Centre
FR25	Basse-Normandie
FR26	Bourgogne
FR3	Nord-Pas-de-Calais
FR41	Lorraine
FR42	Alsace
FR43	Franche-Comté
FR51	Pays de la Loire
FR52	Bretagne
FR53	Poitou-Charentes
FR61	Aquitaine
FR62	Midi-Pyrénées
FR63	Limousin
FR71	Rhône-Alpes
FR72	Auvergne
FR81	Languedoc-Roussillon
FR82	Provence-Alpes-Côte d'Azur
FI12	Etelä-Suomi
FI13	Itä-Suomi
FI15	Pohjois-Suomi
IT11	Piemonte

IT13	Liguria
IT2	Lombardia
IT32	Veneto
IT33	Friuli-Venezia Giulia
IT4	Emilia-Romagna
IT51	Toscana
IT52	Umbria
IT53	Marche
IT6	Lazio
IT71	Abruzzo
IT8	Campania
IT91	Puglia
IT92	Basilicata
NL11	Groningen
NL21	Overijssel
NL22	Gelderland
NL23	Flevoland
NL31	Utrecht
NL32	Noord-Holland
NL33	Zuid-Holland
NL34	Zeeland
NL41	Noord-Brabant
NL42	Limburg (NL)
PT11	Norte
PT13	Lisboa e Vale do Tejo