Institutional Quality and the Effectiveness of EU Funds for Innovation in Italy

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Master Thesis

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Abstract:

Innovation has been shown to be a crucial determinant for growth and convergence, motivating the EU to devote massive spendings towards the promotion of innovation in the European regions. In the case of Italy, especially the South has been targeted for co-financing of innovation projects with EU money. Several papers have emphasized the relevance of institutional quality at the local level for the effectiveness of EU funds. In this paper, I will test whether institutions have had a role for funds to affect the innovation target by measuring innovation output with patents. In doing so, I will use the NUTS 2 - and NUTS 3 - regions in Italy as geographical units, as Italy has been a large recipient of funds in the past, including the two programming periods under analysis, 2007-2013 and 2014-2020. Controlling for spatial spillovers and addressing endogeneity, findings indicate a limited role for EU funds to promote innovation in Italy. Institutions seem to play a role only in the short-term and under certain assumptions about the time lag of the effect, with high-quality institutions being able to amplify EU funds' impact on patents.

Keywords: Innovation, Patents, Institutional quality, Italy, European Structural Funds, Regional Knowledge Production Function

JEL classifications: C33, O52, O31, O38, R11

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1. Introduction

The North-South divide in Italy is apparent in many characteristics that are defining for economic development. In most of the indicators one can imagine, Northern Italy is performing far better than its neighboring regions in the South. Hence, while Rolfo and Calabrese (2006, 346) show that Northern regions such as Lombardy, Piedmont and Lazio represent innovation leaders in the country, Southern regions such as Campania, Sicily, and Calabria lead in unemployment rates (Eurostat, 2022a).

Whereas some argue that this divide emerged after the reunification of the country in 1861, others are convinced that the economic gap has persisted long before (Federico, Nuvolari, and Vasta, 2017). Nowadays, Southern Italy is often used equivalently with the term “Mezzogiorno” that includes the eight regions Basilicata, Campania, Abruzzo, Molise, Sicily, Puglia, Sardinia, and Calabria. These regions largely coincide with the “Kingdom of Naples” that was in place until the reunification of the country and is likely to have contributed to the lagging development of the South persisting until today (Britannica, 2022). Figure 1 illustrates the differences in regional GDP per capita in 2020.

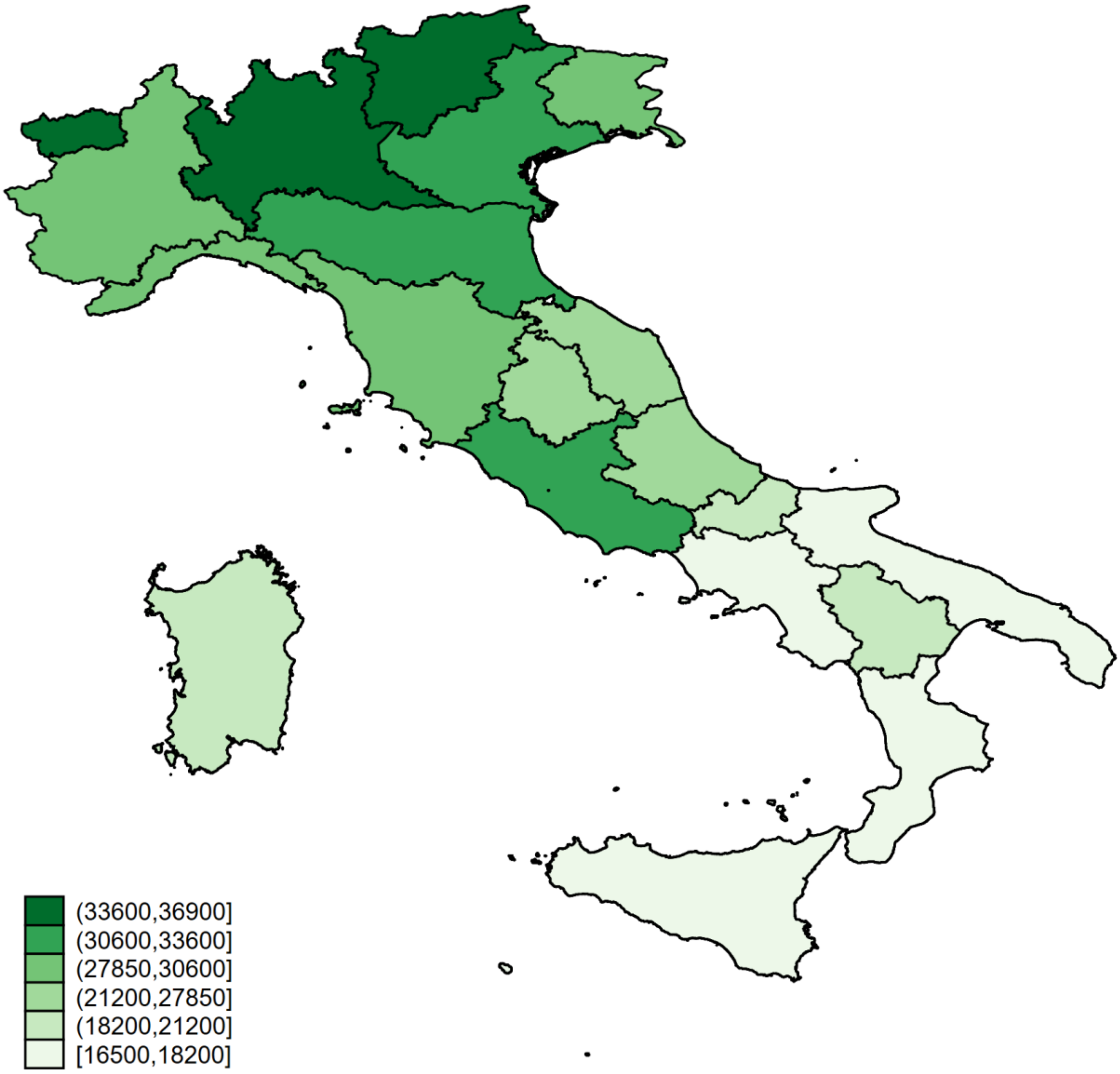

Figure 1: Regional GDP p.c. (€) in the Italian regions in 2020. Source: Own graph, based on data from Eurostat (2022b).

To fight differences in development and achieve growth convergence, technological progress has been shown, e.g., in the influential paper by Romer (1990), to be the key factor ensuring growth in the long term. Given the positive external effects characterizing the research necessary for technological progress and innovations, the paper also emphasizes that incentives must be provided to reach the socially optimal amount of research in a society. In line with this idea, and the promotion of convergence in Italy, large amounts of EU funding have aimed at supporting research and innovation. Funds supporting research and innovation from the EU almost exclusively stem from the European Regional Development Fund (ERDF). The relevance of payments from the ERDF for Italy is shown by the fact that it is the third-largest receiver of funding, following Poland and Spain in the period 2014-2020 (European Commission, 2022b). Out of the roughly 35 billion € of funding in this period, around 36% have been spent on projects promoting research and innovation. This share of ERDF funding has increased from 24% in the programming period 2007-2013, reflecting the increasing importance of this field for Cohesion Policy (OpenCoesione, 2022a).

ERDF funds are allocated at the regional level, coinciding with the NUTS 2 classification in Italy (Solís-Baltodano, Gímenez-Gómez, Peris, 2022). To achieve cohesion, the EU aims to devote more spendings to co-finance projects in the Southern regions, with the goal of enabling them to catch up with the North. For this reason, Figure 2 shows how spendings developed over time in the period 2007-2020, separated by Northern[1] and Southern regions.

[1] The Northern regions include the remaining ones that have not been mentioned as part of the “Mezzogiorno”: Piedmont, Lazio, Trentino-Alto Adige, Tuscany, Umbria, Veneto, Lombardy, Liguria, Emilia-Romagna, Friuli-Venezia-Giulia, Marche and Aosta Valley. While being part of the NUTS 2 classification, the small Northern region of Bolzano is not part of the analysis due to reasons of data availability.

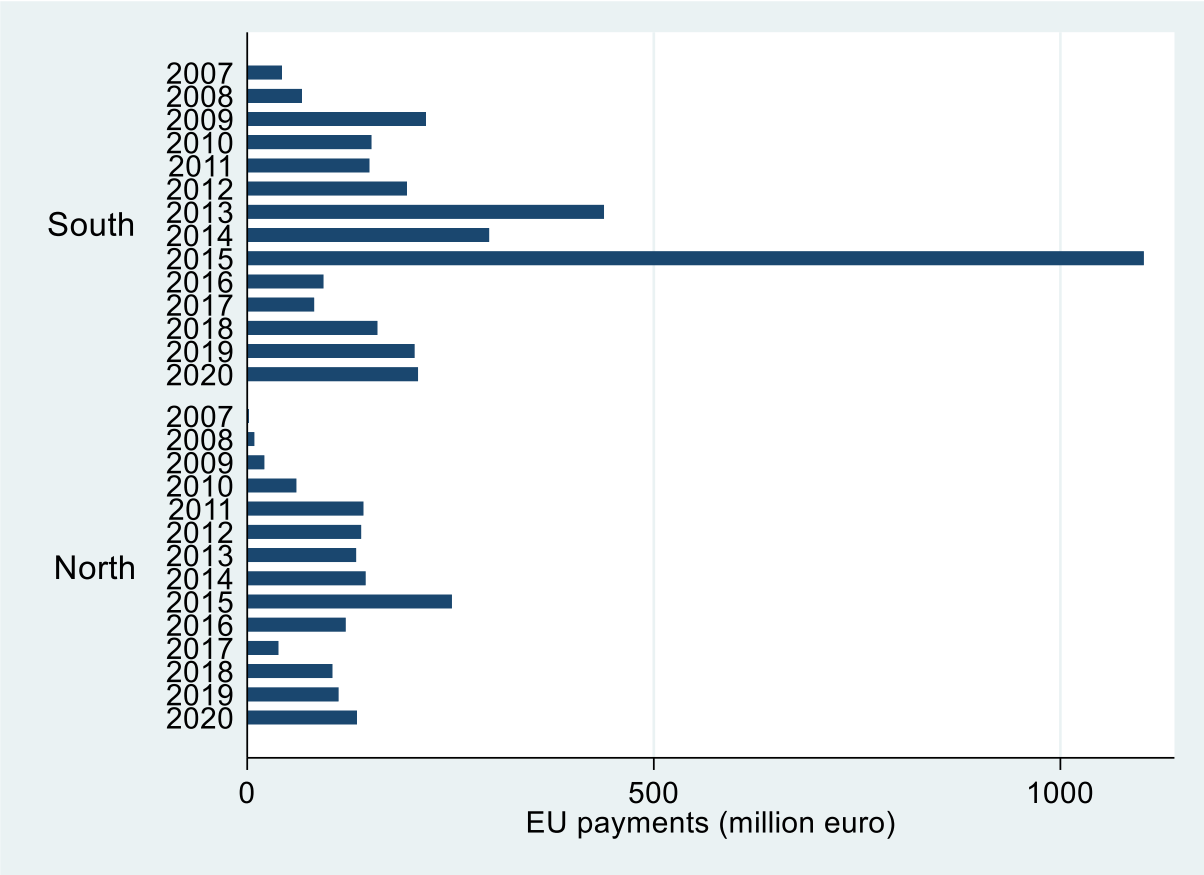

Figure 2: Spendings of EU funds for innovation projects in Northern/Southern Italy, 2007-2020. Source: Own graph, based on data from OpenCoesione (2022c)

While the South has, in accordance with the convergence goal, spent more EU funds in total, the spending seems to be more smoothly distributed in the North. As shown by past evaluations of the effectiveness of the mentioned funds, institutional factors most likely play a role to explain this heterogenous spending pattern between Northern and Southern regions. In this regard, the administration, distribution, and the most efficient use of such funds are likely to be problematic in regions with worse institutions. Evidence from the literature for this assumption will be presented in Section 3.3.

Looking at the two programming periods 2007-2013 and 2014-2020, this analysis will investigate the effects of EU funds targeted to research and innovation on the innovations in the Italian regions, which are proxied by patents. To do so, I will look at all innovation projects in that period which received co-financing from any public source, meaning EU, national, or regional funds, where the latter two funding sources can be confounders of the effect from EU funds and are therefore important to include. Additionally, the information on how much of the costs for the publicly supported projects have been financed by the firm executing the innovation project will be considered. These costs are labeled as the private amount for co-financing, so the contribution of the firm itself to the project. Importantly, this analysis will add to the literature by using a rarely considered database with detailed project data for the relatively underdiscussed funding priority of innovation. Constituting another novelty, this will be done using two alternative geographical scales. Taking into consideration the structural differences of Northern and Southern Italy, including their institutional quality (IQ), I hypothesize that funding from the EU in the form of the ERDF has been more effective in regions with stronger institutions, giving a natural advantage to the North in terms of fund effectiveness.

To evaluate the hypothesis, Section 2 will provide an overview of the literature. Section 3 presents the institutional framework focusing on policies promoting innovation in Italy. Sections 4, 5, and 6 deal with the empirical framework, data and variables, and a brief descriptive analysis of the data, respectively. In Section 7, the results will be presented. Section 8 provides points that deserve to be discussed regarding limitations of the analysis, while section 9 concludes the paper.

2. Literature Review

The literature on the effectiveness of Cohesion funds is highly concentrated on growth effects of the support. Past works evaluating the funds from Cohesion Policy can be classified as model estimations, analyzing the potential effects of monetary support ex ante, and econometric approaches, applying ex post estimations with the actual money flows from Cohesion Policy. In the former approach, the survey on studies evaluating EU Cohesion Funds by Mohl and Hagen (2009, 6) mentions a possible weakness of those studies, as they typically assume that EU funds lead to increased investment, consequently increasing growth and making the estimations likely to lead to positive results. In the latter approach, there is less dependency on such assumptions if data on actual spendings for co-financing projects with Cohesion funds is available, as it is in this analysis.

One common approach is the estimation of a regression discontinuity design to evaluate funding effects depending on the treatment status of a region. Ferrara et al. (2017) investigate how the funding for research and innovation affected the innovations in a region, which are measured by patent applications. For this, they focus on the consecutive programming periods 1994-1999 and 2000-2006. For the last decades, EU funding has been allocated by the clearly defined 75%-rule, where regions with more than 75% of the average GDP p.c. in the EU are eligible for considerably lower co-financing rates to promote projects. This allows the authors to apply a regression discontinuity design, leading them to the conclusion that the innovation support granted to poorer regions in the EU has enabled them to catch up with richer regions in terms of innovativeness. Becker, Egger and von Ehrlich (2018) estimate the growth effects of being eligible for EU funding and compare such regions to ones having similar characteristics but no eligibility. Using the 75% of European GDP p.c. as the cutoff based on which treatment is assigned, they find that once a region loses funding eligibility, previous growth gains vanish, raising the question about the sustainability of growth effects due to EU funding.

Focusing on the negative impact of the crisis on employment in Southern Italy, Ciani and de Blasio (2015) estimate the employment effects of European Structural Funds. Payments from EU and national funding stem from OpenCoesione (2022), also used as a database in this analysis. Acknowledging that other funding sources could be confounders of the effect of EU payments, they control for national funding in their analysis. Following their conclusion of very limited employment effects due to the funding, the authors recognize that their two-way fixed effects specification is likely to omit factors that are changing over time only within a specific region and are therefore not absorbed by the fixed effects. Such factors could have been particularly important in the crisis-stricken South of Italy.

While the assignment criteria of funding to projects in the different regions are not transparent on the levels of EU, national, and regional support, Coppola et al. (2020) attempt to gain insights about the variables on which basis EU funds are distributed. To do so, they regress regional growth on lagged regional GDP, funding from national and EU sources to promote growth, and region- and time-fixed effects. In addition, they use two sets of controls with variables affecting growth correlated to fund assignment, and variables affecting fund assignment correlated to growth in a region. For the latter category, the authors use a control function approach and assume that funds are randomly distributed among regions, conditional on the mentioned covariates. To only include the relevant variables for fund assignment, they use first the EU funds and then the national funds as a function of a set of variables possibly determining treatment. In consequence, only significant variables are kept for the final regression that led to sufficient explanatory power of the two treatments. The analysis of Coppola et al. (2020) subsequently includes another important factor in this context, namely by interacting the funds in the final regression with a variable reflecting the quality of regional governments. After trying different lags of their funds from EU and national sources, Coppola et al. (2020) find that the specification with the highest fit is obtained when growth in period t depends on funding from national and private sources in t and EU funding in t+1. As a reason, they state that spendings for projects are often reimbursed by EU funds at a later point in time, meaning that EU funds for reimbursement paid out in t+1 have financed projects which were already started in t. The authors find significant, positive impacts of the funds on growth, but an insignificant role for the quality of governments in moderating the effectiveness of Structural Funds.

This finding stands in stark contrast to Rodríguez-Pose and Garcilazo (2015) who execute a two-way fixed effect regression with panel data and find that government quality is important to make EU funds effectively increase economic growth. Similarly, Rodríguez-Pose and Di Cataldo (2015) show that institutions are important determinants for innovativeness in EU-regions. To account for the issue of reverse causality, they apply a System-GMM approach, using the lags of the regressors as instruments and proving that the causality works in the expected direction. Not only is innovation shown to be determined by quality of institutions, also the funds are shown to be used more effectively by regional governments with better IQ. Di Caro and Fratesi (2021) allow for heterogenous treatment effects in their analysis of EU funds on growth in Europe and find that the quality of regional governments is decisive to explain whether EU funds have been effective or not.

A controversial issue is the assumed time lag with which R&D efforts are expected to affect the innovation in a region. There is no consensus in the related literature when it comes to the appropriate time lag. Broekel (2013) looks at R&D subsidies and their effects on innovation efficiency in Germany, assuming a two-year time lag for R&D in a firm to affect its patent applications. While his analysis is on a regional level, Broekel (2013) acknowledges that innovations are made at a smaller scale, motivating him to introduce a set of controls which take into account that differences in innovation across regions might be because of characteristics of the firms. Trying to exclude this possibility, the share of high qualified employees, a region's specialization in a certain industry, total regional employment, number of firms, university graduates' interregional mobility, and the number of public research institutes are considered as regional control variables. Focusing on growth effects of EU funds, Mohl and Hagen (2010) contrast the former approach and use a time lag of up to five years for structural funds, where they use the sum of payments in the years before t as the lagged independent variable. Esposti and Bussoletti (2008) check for convergence in Europe due to the Structural Funds and choose a lag of three years over which they compute the average of EU funds.

3. Institutional Framework

The purpose of EU Cohesion Policy is to reduce social and economic inequalities between the regions. To achieve this goal, around 30% of the EU budget are used, showing the importance of cohesion for the EU, where spendings span from employment, environment, and transport infrastructure to digitization, education, and innovation. On an EU-level, cohesion policy started in 1988 under four principles that are, in a slightly adapted way, still intact today. First, EU assistance was supposed to focus on least-developed regions and a few thematic objectives to support. Second, funds are organized within multi-annual programming periods that are subject to evaluation. Third, additionality of EU funds is emphasized, meaning that EU funds should only be paid out in addition to expenditure by the member states made to support regions with low development levels. In fact, breaches of this principle and the use of EU funds as substitution for national funds, especially in times of crisis, can be found in the literature (European Commission, 2021, 26; Del Bo and Sirtori, 2016, 19). Fourth, partnership of the European Commission, the member states and the regional institutions executing the funded projects is important, to ensure that a common goal is pursued (Brunazzo, 2016).

Cohesion policy in the EU in the form of European Structural and Investment funds (ESIF) consists of five funds in total: The European Regional Development Fund (ERDF) aiming at the EU regions to develop at a similar pace, the European Social Fund (ESF) focusing on human capital and employment, the Cohesion Fund (CF) trying to promote transport infrastructure and the environment in less developed regions, the European Agricultural Fund for Rural Development (EAFRD) providing support for rural areas, and the European Maritime and Fisheries Fund (EMFF) giving financial help to coastal regions in the EU. For the money to reach eligible projects in the regions, the national governments agree on investment priorities for seven-year programming periods with the European Commission. Projects supporting innovation, which are the thematic focus of this paper, are part of the ERDF, where the money coming from the EU is paid out by the national "Rotation Fund" in the case of Italy (European Commission, 2022a).

3.1 Cohesion Policy in Italy

In the programming period 2007-2013, projects in Italy could be financed from the ERDF with up to 75% of the total project costs in the convergence regions, including Sicily, Calabria, Basilicata, Puglia, and Campania at that time (European Commission, 2006). The remaining regions were only eligible for co-financing of up to 50%. A convergence region is defined as a region having less than 75% of the EU-average GDP per capita in PPS (EUR-Lex, 2006). In the succeeding programming period that is also analyzed here, 2014-2020, the maximum co-financing rate for the less-developed regions, which coincide with the convergence regions in the previous period, increased to 80% of the project costs. As an additional category, the transition regions Sardinia, Molise, and Abruzzo were eligible for 60% from the ERDF covering projects' costs, while this rate was at 50% for the remaining more developed regions (European Commission, 2015).

To get a deeper understanding of how the funds are supposed to increase innovation, it is worthwhile to take a look at the types of projects that are co-financed by the EU. Looking at investments from the ERDF aimed at innovation in the programming period 2007-2013 in Italy, the report from the European Commission (2021) presents the policy instruments associated with the ERDF. These include the funding of research projects where science and industry are collaborating, with the reasoning of enabling participating firms to "exploit research results by developing innovative products" (European Commission, 2021, 40). It is therefore reasonable to assume that such projects can have a direct effect on patenting activities in the Italian regions. Another policy instrument is the funding of projects in technology clusters, where firms' innovation is supposed to increase by strengthening synergies between research centers, companies and regional authorities that are located geographically close to each other. By issuing tenders, the goal of policymakers was to reinforce existing technological clusters in a region and to build new ones, e.g., in the form of public-private laboratories for research. One specificity of such technology clusters is that they are highly regionalized and are also coordinated by a regional institution, giving the importance to regional government quality for successful project implementations (European Commission, 2021, 58-61). A third policy instrument consists of investments in research infrastructure, including construction or purchasing equipment necessary for research, but also including training of employees to use the new infrastructure. Universities and research centers were usually taking advantage of such funding opportunities. The idea that policymakers had in mind was to increase the innovation potential in a region, and to develop skills and research institutions in a region (European Commission, 2021, 79).

When evaluating the mentioned policy interventions with a contribution analysis by examining the "Theories of Change" of the policies, the Commission stresses the anticyclical role of the RTD investments, as the crisis induced many companies to reduce investments in R&D. In 2007-2013, spendings on RTD from the ERDF were the primary funding source to support innovation for firms in convergence regions, the poorest regions in the South of Italy. Counteracting the presented principle of additionality of EU funds and thereby criticizing the distribution of funds, the Commission states that RTD co-financing in this period was provided relatively independent of national and regional support. Even though support was substantial, turning the investments into research results has seemed to be less common, leading the Commission to the conclusion that funding helped to sustain R&D, but had little impact on innovations in products, services, or processes (European Commission, 2021, 93). Another role is given to firm size, where large firms are found to have taken advantage of funds better than small firms, as they have more economic power and are generally more able to cooperate with subcontractors in the research process. In particular, turning research results into applications on the market, as it is done when applying for a patent, is said to have been prevented by a delayed disbursement of the EU funds and a low ability of small firms to issue patents (European Commission, 2021, 94).

Focusing on the most recent programming period, Figure 3 shows that, in accordance with the cohesion goal of the European Commission, projects in Southern Italy have received far more ERDF resources than projects in the North. Exceptions are the largest cities not located in the South that have received relatively high financial support, namely Rome, Turin, and Milan. This picture is similar for the preceding period.

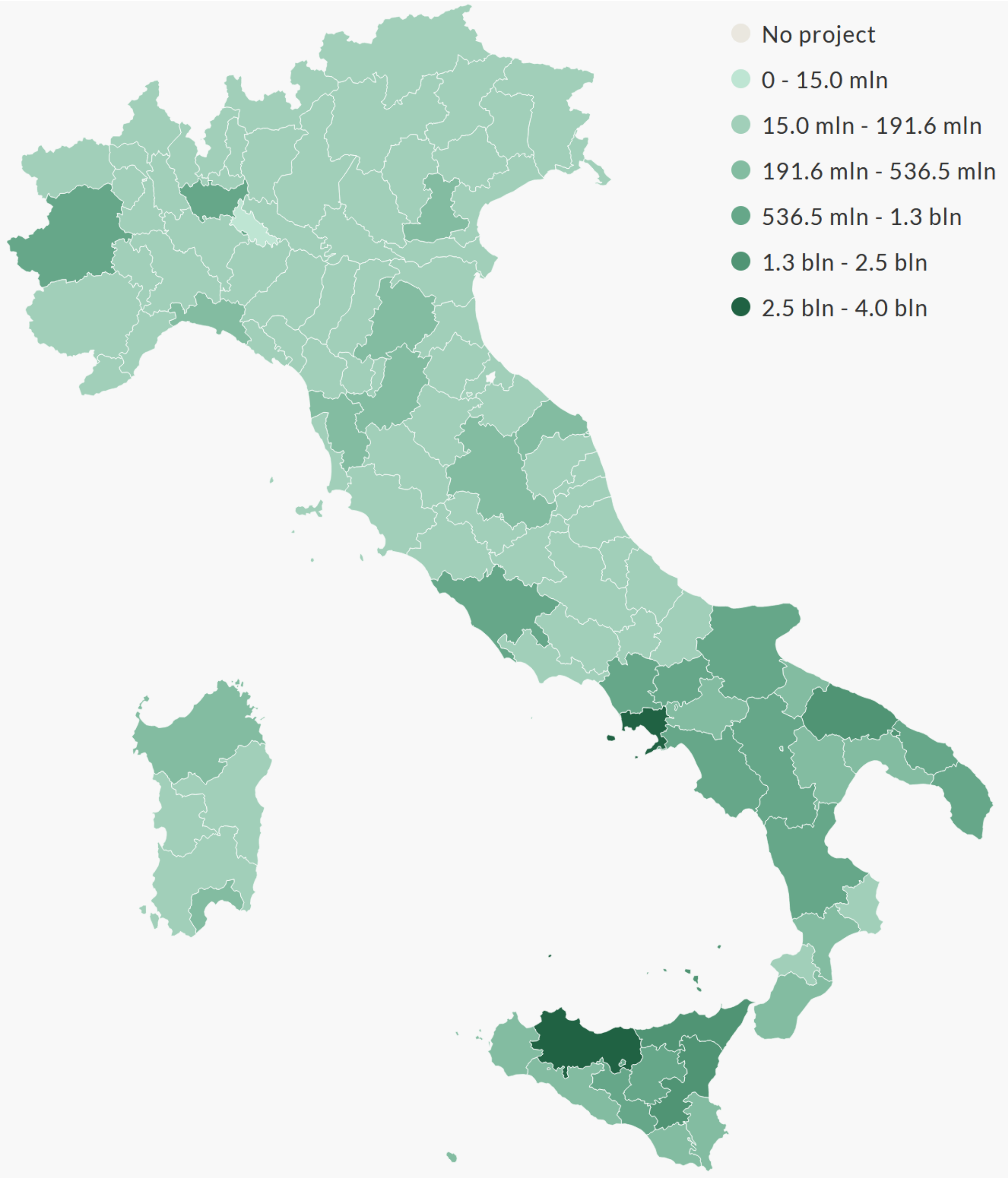

Figure 3: Monetary support (in €) from the ERDF by province, 2014-2020. Source: OpenCoesione (2022b)

Although innovation was mentioned as a goal before, the systematic implementation of innovation as important factor for cohesion policy occurred with the setup of the Lisbon strategy in 2000, aiming at making Europe a competitive, knowledge-based economy while ensuring social cohesion. These ambitions were reflected in the programming period starting in 2007, where convergence of poorer European regions was aimed to be achieved, especially through innovation (Brunazzo, 2016). The fact that focusing on innovation within Cohesion policy started in the programming period 2007-2013 is also confirmed by Wamser, Nam, and Schoenberg (2013, 50). Investigating the determinants of innovation promotion through the EU, they stress that innovation has not been a priority on EU-level in the preceding programming period, 2000-2006. This makes the analysis of the two most recent programming periods for the topic of innovation, as executed in this analysis, highly appropriate, as it is unlikely that results are biased from earlier money flows not shown in the data that could have had an effect with a large time lag. EU aid in the period 2014-2020 was again heavily influenced by the crisis and the struggling economies in Southern Europe. Publishing the "Europe 2020" strategy in 2010, innovation was mentioned as one of the key pillars for strengthening Europe's position in international competition. Specifically, the Commission aimed at improving the access to co-financing for projects in R&D (European Commission, 2010).

For a policy to affect the variable of interest, it is important to look at the channels through which the funding can increase innovation. The data on payments from Structural Funds to support innovation gives insights on how the money is supposed to increase innovation (OpenCoesione, 2022c). Here, payments are classified into 17 categories by the impact they are planned to have on innovation. The complete list of channels is presented in Appendix 1. It can be said that special attention is paid to strengthening innovation in small-and medium-sized enterprises, and that the promotion of RTD is a key point to receive funding. Another supported area is the cooperation of businesses with other institutions, such as universities, aiming at the exploitation of knowledge spillovers to create innovation.

3.2 National and Regional Framework

Besides the seemingly overwhelming importance of EU funds for innovation promotion for Italian firms, the national and regional frameworks also have some importance for this purpose. Rolfo and Calabrese (2006) emphasize that the role of the state is enormous in the Italian R&D system, when it is compared to other nations. Regions started with the implementation of their policies for innovation support in the programming period 2007-2013. While regions have only been assigned with formerly national competencies for policy interventions, the situation has become more complex after 2007, with much more freedom on a regional scale. This freedom tends to be used more actively by Northern and Central regions in Italy when it comes to policies promoting innovation (Caloffi and Bellandi, 2017).

Rolfo and Calabrese (2006) describe universities, research institutions and laboratories, both on a local and on a state level, as the main public actors for Italian research. These organizations are mostly supervised by the Ministry of Education, University and Research (MIUR). With the reform of innovation policies in the year 2000, funding also became achievable for projects that were submitted in cooperation between public research institutions and private firms. With this major change, the temporary stay of researchers from public institutions in private firms also became eligible for support, just as incentivizing small- and medium-sized enterprises (SMEs) to employ researchers or to start a cooperation with public agencies for research. Hence, it becomes clear that the reform had the clear goal of simplifying joint research of public and private organizations. Particular attention was paid to the distinction of responsibilities for the state and for the regions (Rolfo and Calabrese, 2006, 347-349).

National policies include the "Programma Operativo Nazionale Ricerca e Competitività" that specifically aims at the less developed regions in the South and is mostly co-financed by EU funds from the ERDF (OpenCoesione, 2022). Since the 2000s, technological districts have also been a major focus of national innovation policies, aiming at centralized areas where universities, research-centers and businesses were supposed to benefit from each other's presence, increasing innovation. Such attempts were complemented by promoting collaborations of universities and firms in specific industries, with questionable results. Other policies on a national scale include subsidized loans and grants that are facilitating the execution of innovation projects for firms, often provided by the National Guarantee Fund (Caloffi and Bellandi, 2017, 135-138). Recently, for 2015-2020, Italy's policy for research and innovation has been guided by the National Research Programme, which has been set up by the MIUR. Funds here include some exclusively national initiatives, or others that are co-financed by European Structural Funds. More importantly, indirect tax incentives are increasingly provided, trying to facilitate R&D, patent applications or investments in human capital and machines. As another example, the "patent box" was introduced in 2015, trying to incentivize patent applications by giving tax exemptions for firms' income from intellectual property rights. Available empirical evidence casts doubts about any impact of this policy on firms' innovation (Nascia and Pianta, 2018).

The broader objectives of national innovation policies have been defined prior to the period under analysis in this paper, namely from 2003 to 2006 within the National Research Plan. With the objective of a new strategy for research in Science and Technology (S&T), the most important actors of research in Italy, also including private firms next to the range of public institutions, have jointly determined how funding from the state should be distributed. To promote this goal, the focus has been put on four strategies. To begin with, training human capital and enabling it to push forward research is a main objective. Secondly, cooperation of research institutions, but also public-private research cooperation and strengthening entrepreneurship have been aimed at. Special relevance also accrued to the third pillar, consisting of more industrial research and the transformation of research outputs to products, which has a special relevance for the outcome variable chosen in this analysis, the patent applications. Lastly, product and process innovations in SMEs have been defined as a field for the funding to focus on (Rolfo and Calabrese, 2006, 350-352).

Regional policies for innovation promotion are generally organized in agreements that are negotiated between the regions and the state. These negotiations clarify which areas of funding are in the interest of both, region and state, and which ones are only of regional interest and therefore only receive regional funding. Here, clear differences between Northern and Southern regions emerge. Whereas regional programmes in the North are more commonly organized in unilateral agreements with the state, for the Southern regions, there is the National Operational Programme for Research (NOPR), funded entirely by the national Rotation Fund and the ERDF through the EU. After only including Apulia, Calabria, Sardinia, Sicily, Basilicata, and Campania initially, the funding from this source has been extended to Molise and Abruzzo in the programming period 2014-2020 (EFSe, 2020). Thematically, the NOPR aimed at increasing research in private firms, improving the equipment necessary for research, and opening ways for people to improve their human capital with a focus on enabling them to strengthen innovation activities in the regions (Rolfo and Calabrese, 2006, 353-354).

Funding for all regions in Italy additionally comes from the Development and Cohesion Fund ("Fondo per lo Sviluppo e Coesione", FSC) usually originating from regional or national monetary sources, in addition to private co-financing. In the programming period 2014-2020, most projects funded by the FSC have been paid with national resources, while the redistributive character of the fund is ensured through the assignment of 80% of its resources to the area of the "Mezzogiorno", whereas the residual amount goes to Northern regions (Ministro per il Sud e la Coesione territoriale, 2022). Other than that, regional financing for innovative projects is usually provided as co-financing in the framework of the structural funds of the European Union (OpenCoesione, 2022).

In any case, the framework for innovation promotion in Italy is too complex to describe it in its completeness at this point. As summarized by Rodríguez-Pose and Di Cataldo (2015, 677), "innovation policies are today more and more defined through a complex process of multilevel agreements, involving negotiations at the sub-national, national and supranational levels". More importantly, a complete collection of all innovation-related payments from policies on EU, national, and regional level in Italy is available in the dataset used in the empirical analysis (OpenCoesione, 2022c).

3.3 The Relevance of Institutions

Stemming from the mentioned dataset, Figure 4 shows the payments by sources to support innovation projects in Italy. Payments in 2015 are far higher than in the other periods. The importance of national and regional funding sources stressed in the previous section is confirmed in the figure, although money from the EU constitutes the most important part of co-financing for innovation projects, followed by resources provided by the Italian state. Regional spendings have a lower relevance in relative terms.

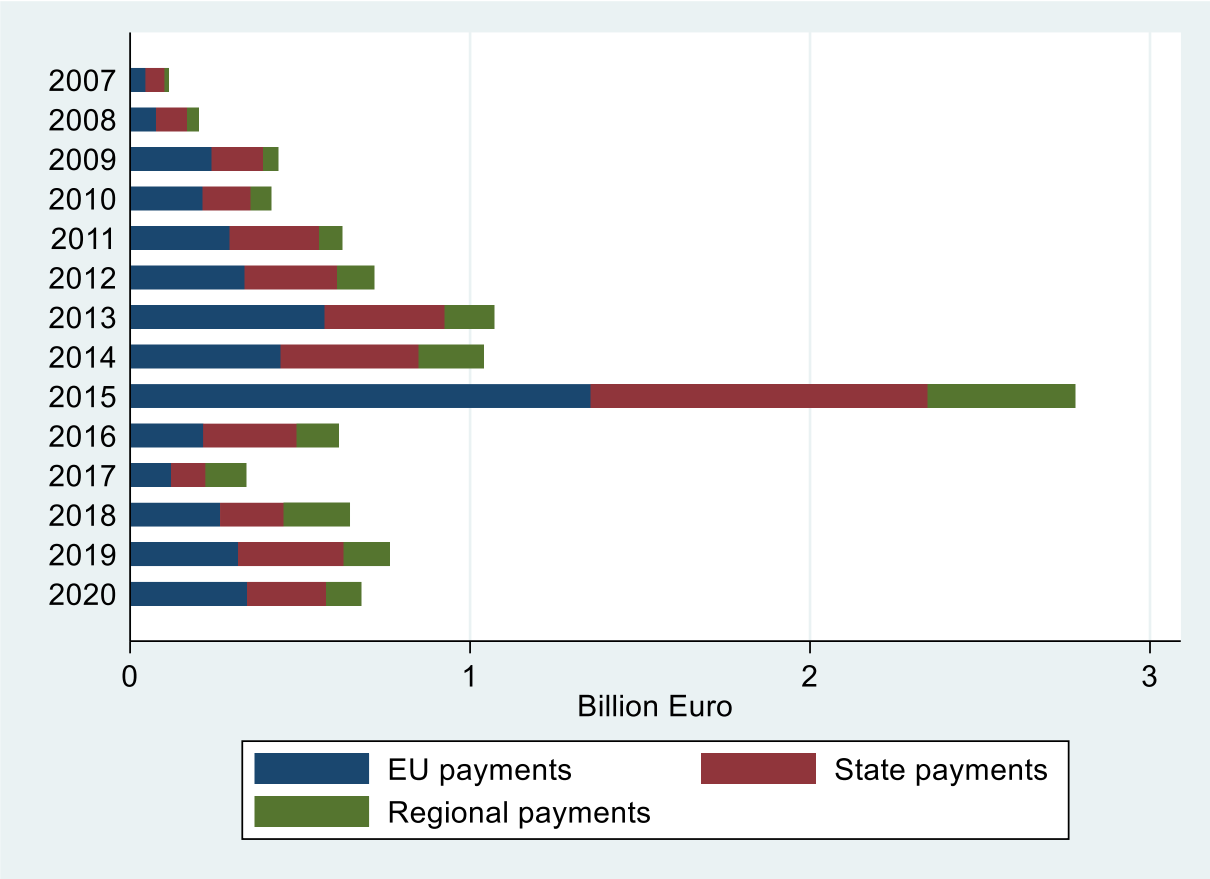

Figure 4: Payments to co-finance Italian research and innovation projects (billion euro), 2007-2020. Source: Own graph, data from OpenCoesione (2022c)

A look at Figure 2 makes it easy to see what drove the peak in funds for research and innovation projects in 2015 observed in Figure 4. Mostly the unequal spending pattern in the South is responsible for this picture. To understand the massive peak of spending in the South in 2015, the "N+2"-rule of EU funds must be introduced at this point.

Within the framework of seven-year programming periods, in which also ERDF spending is organized, funds in the period 2007-2013 have been provided according to the "N+2"-rule. This rule has been implemented by the EU to prevent misuse of funds and states that resources from the EU must be spent within two years after they were received by the managing authorities in the member states. If money is not spent in these two years, it must be returned to the EU and will be deducted from the future budget provided to the operational programme which has received more than it has spent. In the most recently finished programming period 2014-2020, this rule has been extended to "N+3", meaning that money must be spent within three years after receipt (Leonardi and Holguin 2016, 439). For this reason, funds within the 2014-2020 period can be spent on projects until 2023. One could therefore suspect that the rise in spendings in 2015 is connected to the termination of the 2007-2013 period, to which a maximum of two years was added, so until 2015, before budgets had to be returned to the EU according to the "N+2"-rule. The fact that the rise in 2015 is so much stronger in the South than in the North, even relative to payments made before and after the surge, could indicate that Southern regions are generally slower in assigning EU money to projects and to organize the spending on time. Such a “last-minute” spending pattern in the South is partly confirmed in a report by Lo Piano, Chifari, and Saltelli (2018), made for the European Commission. In this report, regions in Southern Italy are found to spend EU funds more concentrated at the end of programming periods, rather than smoothly distributed over the whole programming period, as it is done more so in the Northern regions. According to the report, also the time that passes between the receipt of the funds and spending them on actual projects is lower in regions that tend to spend funds earlier in a programming period, which applies to the Northern regions. In Southern regions, on the other hand, a longer time passes before payments from the EU are spent on projects, and the spendings are more concentrated at the end of programming periods.

Lo Piano, Chifari, and Saltelli (2018, 34) also state the assumption that, the later regions spend the EU funds, the lower is their pace in spending and the lower is the quality with which the funds are spent. Such a lower quality of spending could also be induced by time pressure due to the “N+2”-rule, incentivizing regions to spend money even on ineffective projects that might not have been carefully evaluated in advance, just so funding in the next programming period is not cut for these regions. Evidence for lower effectiveness of spending in the South comes from the evaluation of EU funds devoted to Research and Technological Development (RTD) in the period 2007-2013 in Italy (European Commission, 2021). The report states that funds for the support of RTD have been ineffective in the South, with one of the main reasons being issues in the public administration of funds, their inefficiencies, just as their lack of capacities to deal with assignment and distribution of funds. In consequence, the quality of institutions responsible for assigning the money to promising projects, organizing spending, and executing it seems to play a key role when it comes to the effectiveness of EU funds promoting research and innovation.

4. Empirical Framework

As discussed by Romer (1990) in the development of an endogenous growth model, technological change without physical capital is depending on the technological level in an economy and the human capital available to extend the technological level. When adding the quality of government as another variable decisive for technological change, then the following log-linearized version of the model in Romer (1990) can be obtained, as in Rodríguez-Pose and Di Cataldo (2015, 679), reflecting the basis for the regional knowledge production function used in this analysis.

$$ln\ g_{A_t} = (\beta_1 - 1) * \ln A_t + \beta_2 * \ln(a_L * L_t) + \beta_3 * \ln IQ_t \quad (1)$$

Here, $g_{A_t} = \frac{\dot{A}_t}{A_t}$ can be interpreted as the growth rate of the innovation capacity A at time t, and the product $a_L * L_t$ represents the share of employees in the production of new knowledge. IQ_t stands for the institutional quality in t. When applying this equation to the regional framework, widening the definition of $a_L * L_t$ to include all the local factors that affect a region's ability to generate innovation, and adding investments in R&D, including possible co-financing, to the equation, the following Equation 2 can be obtained. This, again, was done similarly in Rodríguez-Pose and Di Cataldo (2015, 679).

$$\Delta\, ln\, Patents_{i,t} = (\beta_1 - 1) * \ln Patents_{i,t-1} + \beta_2 * \ln R\&D_{i,t-k} + \beta_3 * W * \ln R\&D_{i,t-k} + \beta_4 * LF_{i,t-k} + \beta_5 * IQ_{i,t-k} + \mu_i + \omega_t + \varepsilon_{i,t} \qquad (2)$$

Here, the growth in patents, $\Delta \ln Patents_{i,t} = \ln Patents_{i,t} - \ln Patents_{i,t-1}$ is used as a proxy for innovation outputs. The regressors, as it is done in Mohl and Hagen (2010, 357), are lagged, in the general case, by k periods, including the local factors affecting a region's innovation capacity, $LF_{i,t-k}$, where the variables included as local factors will be described in the next section. A time lag is applied as the generation of innovation outputs usually takes time, so the outputs in t can be assumed to depend on local conditions at an earlier point in time. The term W stands for a spatial weight matrix, as the R&D expenditures in region i can represent an externality and affect innovation in, e.g., neighboring regions. Finally, the terms μ_i, ω_t, and $\varepsilon_{i,t}$ are the region-fixed effects, year-fixed effects, and the idiosyncratic error term, respectively.

A few comments about the time lag of funds to affect patents are in place. The finishing year of a project is the one indicating in which year a project took place in the dataset used here, but it could be suspected that some innovation effects already took place during the execution of the project, prior to its finalization. Given that the average length of projects in the data is around one year, including a lag of one year between finalization and expected effects on patents could be interpreted as giving the project around two years to affect patenting in the region. Among the papers discussing effects of public money on innovation, this is in line with Broekel (2013). Still, Esposti and Bussoletti (2008) find the best fit with a lag of three years, and Rodríguez-Pose and Di Cataldo (2015) even include R&D expenditures for the same year as their outcome, growth in patents. Regarding the controls in the equations, there is no consensus about the time lag to be included either. Coppola et al. (2020) include controls with a one-year time lag, while Rodríguez-Pose and Di Cataldo (2015) do so in the same year as the outcome variable.

The approach executed here will experiment with several time lags, although controls will be preferably included at an earlier time than the treatment, to prevent biases from bad controls, a risk emphasized by Mohl and Hagen (2009). One example for a bad control is the number of researchers in a region. This might be reasonable to include as they most likely affect the patenting patterns and simultaneously are correlated with the amount of structural funds for innovation that a region receives. The latter correlation could simply arise from regions with more researchers proposing more projects that are eligible for innovation support, as these regions have the human capital to execute these projects. On the other hand, the correlation of the funds a region received and the number of researchers in a region could arise from more funds leading to increasing employment of researchers to make use of these funds, who will then likely affect the level of innovation. In this latter case, the channel of more researchers being determined by the receipt of funding would, if included, absorb part of the causal effect of funds on innovation. Hence, it is important to be careful with the inclusion of control variables.

One way to address this problem is the use of time lags in the regression. Coming back to the example, the number of researchers in a region in 2009 should not be affected by the amount of funds received in 2010, as the receipt of funds lies in the future. Nevertheless, although a firm in a region might receive the money in 2010, it might anticipate the receipt even before 2009, or the firm might have planned the project for a longer time in advance. In such a case, time lags are not solving the problem, and more advanced techniques for regression analysis should be chosen. As presented in the literature review, one way is an Instrumental Variable-approach, which will be executed at a later stage of this analysis.

As the analysis in done on a regional scale, and not with the innovating firms as cross-section units, it is crucial to control for firms being different in the different regions, which is why a large set of controls has been adopted. Here, it is important to control for characteristics that correlate with patents and innovation funding at the same time. Special care should be taken of structural characteristics of the regions, as there might be some characteristics of certain regions that make them more likely to issue patents than other regions. If these characteristics are not constant over time, then they are not captured by the region-fixed effects. Additionally, if some of these characteristics are not constant across regions, then the time-fixed effects would not capture them. If both holds for a variable, then the omission of that variable would lead to a correlation of the dependent variable with the error term and cause biased results.

An additional threat for the validity of the specification comes from the Nickell-bias in the case of a dynamic specification (Nickell, 1981). This is so because the lagged dependent variable and the region-fixed effects are correlated, leading to a downward bias of the lagged dependent variable's coefficient. This bias becomes worse for few time periods considered and a large persistence of the dependent variable over time. Similarly, the coefficients of the regressors, particularly of the funding sources included here, can be biased if they are correlated with the lagged dependent variable. Although this upward bias for the coefficients of the regressors should be smaller than the bias in the lagged dependent variable, it worsens when regressors are persistent (Bun and Kiviet, 2003).

In addition, using patents as a proxy for innovation output can be criticized for several reasons. Private expenditure in R&D or funding for R&D-associated projects does not necessarily result in innovations that can be patented, especially when these innovations are related to new processes or organizational innovations. This is because patents are more common to protect product innovations (Jensen and Webster, 2009, 262). For this reason, the latter authors find that patents are especially well-suited to proxy the innovativeness of the manufacturing sector, which relies on product innovations more than other sectors. Jensen and Webster (2009, 256) add that patents are an incomplete innovation proxy also because other forms of protecting intellectual property, such as a copyright, are more common in some industries. Additionally, small firms are mentioned to often lack financial resources to apply for patents, forcing them to choose other modes of protecting property rights. Carlino and Kerr (2015, 357) add that the value of patents is very heterogenous, with typically few patents having a notable impact on economic development. Despite these disadvantages, patents have been shown to be highly correlated with the economic performance of firms, which matters particularly for the convergence goal and firms' competitiveness in Southern Italy. Also, as patent applications are costly, the invention behind a patent is likely to yield actual added value if the company is willing to protect it with a patent (Grzegorczyk and Glowinski, 2016, 32). Additionally, patents have the highest data availability among outputs of inventive activities and are therefore used as a proxy for innovation output in this analysis.

To account for the drawbacks of patents as innovation proxy, I will use the number of researchers employed in a region as alternative dependent variable. This can be assumed to be directly affected by innovation co-financing, as hiring more research personnel was one of the investment priorities. Although researchers are an input for the innovation process, they can still give insights about whether the policy influenced these inputs or not, with the number of researchers being closely connected to innovation.

In a second subsection, after looking at effects on the regional level, the analysis will turn to the provincial level. First, this allows to control for spatial spillovers of the EU funds, being the co-financing source of interest in this analysis. Second, innovation networks in Italy are very localized, such that the provincial analysis will be more likely to take research units, e.g., technological districts into account that might have driven the results on the regional level. On the negative side, this leads to some zero observations in the dependent variable. As the estimation with zeros in the dependent variable has been shown to lead to biased estimates, I will address this issue with a Poisson regression (Santos-Silva and Tenreyro, 2006). Trying to exclude endogeneity caused by, in addition to the reasons mentioned above, reverse causality, I will finish the empirical analysis with an IV-approach in the form of a System-GMM estimation.

5. Data and Variables

Overall, and after excluding the very few interregional projects that would have been hard to assign to a single region, the analysis is based on 53,260 projects from 2007 to 2021. These projects are then classified by the NUTS 2 region they have been executed in and by the year in which they have been finished. Even though the included variables will be described at this point, the precise definitions and sources of the variables can be found in Appendix 2.

The dependent variable in the analysis is patents applied for under the Patent Cooperation Treaty (PCT). As it is common in the related literature, e.g., Mohl and Hagen (2010) or Rodríguez-Pose and Di Cataldo (2015), the variable is corrected by the economic size of the region. For this reason, patents are divided by the regional GDP in PPS. To obtain the specification presented in the former section, patents as a dependent variable are expressed in changes from t-1 to t, after logs are taken.

Similarly, the independent variable of interest, EU co-financing of innovation projects, is divided by the regional GDP in PPS and expressed in logs. The same is done for the other funding sources of innovation projects, namely state, regional, and private funds. All sources for funding of innovation projects are important to include, as only including the European co-financing could lead to an overestimation of its innovation effect because some of the benefits accrue to one of the other funding sources. As several regions received no money in some particularly early years of the analysis, to still be able to take logs, one has been added before doing the log-transformation. Adding one is insignificant when compared to the usually large magnitudes of payments for innovation projects and running regressions without the transformation has shown to yield only marginally different estimations. Controls that are specified in levels are also expressed in logs in the estimation. OpenCoesione (2022c) provides this analysis with data for the two most recently concluded programming periods, 2007-2013 and 2014-2020. In the database, every single project related to Italian Cohesion policy is included, with the amount of money for it financed by the EU, nationally, regionally or by the supported firm itself, reflected in private payments. The data inform about starting and ending date of the project, the thematic objective, the firm supported, and its location in terms of the NUTS 2 and NUTS 3 region. In addition, every project contains information about the fund under which spending is organized. I chose to restrict the analysis to projects that are already executed with the thematic focus on innovation, as only for these projects an impact on innovation in the form of patents can be expected. In the thematic priority of innovation, the by far most common way of financing the innovation support is the ERDF. Within the ERDF, projects are financed by several possible sources. Most importantly, the structural fund payments in the two programming periods by the EU are used to finance projects. Complementing the EU payments from the structural fund, money from the Rotation Fund from the national level, from the regional level, and from private financing can add up to the amount paid by the EU. In contrast, projects financed through the "Development and Cohesion Plans" only come from the respective fund that is financed nationally. Projects under this framework can, again, be co-financed through regional and private sources, but the EU is not involved here. As an alternative source of funding, there are projects financed exclusively by "ordinary national resources", where no other sources of financing are required. Similarly, projects financed by the "Action Plan for Cohesion Programmes" are only receiving money from national sources and are complemented by private co-financing (OpenCoesione, 2022c).

Special attention should be devoted to the IQ of regions as moderator for the effectiveness of Cohesion Funds. The literature review has shown that the quality of regional institutions is an increasingly discussed factor that can influence the effect of structural funds on the targeted outcome variable. In this regard, the analysis includes the Institutional Quality Index (IQI) by Nifo and Vecchione (2015), which is similar to the World Governance Indicator (WGI) by the World Bank. In the IQI, institutional quality is an indicator made up by scores in five different fields for each region and province: Corruption, voice and accountability, government effectiveness, regulatory quality, and rule of law. These classifications are similar in the approach by Rodríguez-Pose and Di Cataldo (2015) and the authors provide the framework of how four out of the five components can influence funds' effectiveness.

Government effectiveness is argued to be decisive for an increasingly regional implementation of the Structural Funds. In this way, the regional government's capacity to develop an appropriate strategy for innovation, the administration of funds, project monitoring, and the financial resources for all these tasks become crucial for a successful implementation at the regional level. The regions' rule of law also influences overall IQ and is argued to affect firms' willingness to invest in innovation projects by providing suitable conditions for the protection of property rights, including the efficiency of judiciary processes at the regional level when it comes to intellectual property rights. Corruption can impede the innovative capacity of a region by not assigning funds to the most promising projects, but according to the wishes of interest groups and elites in a region. Ensuring the independence of regional institutions responsible for the administration of funds is therefore crucial for the policy's effectiveness. Voice and accountability are important to ensure for regional governments as politicians might have larger incentives for rent-seeking due to them being closer to interest groups at the local level. The assignment of funds therefore must be organized in a way such that the decision-makers are held accountable to the public (Rodríguez-Pose and Di Cataldo, 2015, 676-678).

As mentioned in the previous section, Omitted Variable Bias (OVB) must be addressed by including control variables. This must be done while keeping in mind the above presented problem of bad controls. In doing so, the set of local factors mentioned in section 4 will be presented now.

The analysis will include the employment share of the regions in S&T. Regions with a higher value in this variable can be assumed to be better equipped for R&D, making it more likely that patents are issued in those regions. Additionally, funds devoted to the promotion of research are more likely to be assigned to regions where the infrastructure for research is well-developed, and where the share of people working in S&T is high. This control also serves as a proxy for the share of employment in high-tech manufacturing, used in Rodríguez-Pose and Di Cataldo (2015). Just as the authors mentioned, I will include the share of employment in agriculture as control, as regions might become more industrialized in the period under consideration, leading to lower values for this variable and a higher propensity for patenting.

Similarly, larger firms are more likely to have the financial possibilities to apply for patents and, at the same time, can be assumed to be more likely to successfully apply for funding, e.g., from the EU (Beugelsdijk, 2007, 195). Hence, the average firm size in each region, measured as the number of employees per firm, will be included.

In addition to that, controlling for the population size of a region can help to control for the size of the regional economy. Despite this, it turned out insignificant in the regressions, possibly due to high correlation with other controls. Therefore, it will not be included in the empirical analysis.

An important criterion for the assignment of funds is the regional GDP per capita. As this variable is also correlated with the number of patents in a region, it is crucial to consider it as control. On the other hand, some of the already included variables as tertiary education, the number of researchers, or the share of employment in agriculture can be seen as predictors of GDP per capita in a region. Including both types of variables at the same time, predictors of GDP per capita and the variable itself, could lead to problems of very high collinearity, as GDP and its predictors could capture the same variation of the dependent variable. Hence, the empirical analysis will experiment with the inclusion of predictors of GDP per capita and the variable itself.

The regional unemployment rate can be important to determine the amount of funds received (Wamser, Nam, and Schoenberg, 2013). It is also considered by Rodríguez-Pose and Di Cataldo (2015) and will therefore be included, as it reflects characteristics of the labor market of a region that is crucial for innovation. This also holds for the employment density of a region, that is shown to affect patents in Carlino, Chatterjee, and Hunt (2007). Regions with a higher density also tend to receive more public co-financing of projects.

Important confounders for the effect of funds can be composed of the private spending on R&D in the regions, independent of funding for innovation projects. Reflecting innovation inputs, Rodríguez-Pose and Di Cataldo (2015) use the private expenditure on R&D as a control. Additionally, this analysis will consider R&D expenditure from the government and the tertiary education sector, as increasing expenditures could be related to improving infrastructure for innovation and a higher propensity to patent in some regions. Additionally, regions with a higher share of tertiary educated people and more researchers can be assumed to provide better conditions for patenting.

Although surely not all the variables can be taken into account here to reflect regional heterogeneity in the propensity to innovate, the regional characteristics that are constant over time will be absorbed by the region-fixed effects and should therefore reduce the problem of OVB. Certain shocks affecting all regions in a year will be picked up by the year-fixed effects.

6. Descriptive Analysis

Table 1 shows the descriptive statistics of the variables in absolute values without logs, including their mean, the standard deviation, minimum, maximum, and the number of observations.

Summary statistics

	Mean	SD	Min	Max	N
Patents	1.69	1.143	.098	5.634	300
EU funds	17483989	38671394	0	3.050e+08	300
State funds	13407905	24233701	0	2.240e+08	300
Region funds	6220687.6	16052255	0	1.330e+08	300
Private funds	45795865	3.663e+08	0	6.310e+09	300
Employment share in agriculture	.055	.039	.014	.185	260
Employment density	67.284	41.612	16.161	183.217	280
Unemployment rate	10.246	4.989	2.9	23.5	280
Population	2964.337	2451.265	124.6	10019.2	300
Tertiary education share	16.646	3.21	10.8	27	280
Researchers	5953.067	6301.23	143	32474	260
Institutional Quality	.58	.239	.072	.982	260
Employment share in Science and Technology	.312	.03	.254	.388	280
GDP p.c.	26742.5	6818.035	16300	39700	280
Firm size	5.7	.415	4.872	7.341	260
Government R&D expenditure	46.475	52.662	5.1	244.9	260
Tertiary education R&D expenditure	95.494	33.089	25.5	184.9	255
Private R&D expenditure	164.827	134.893	3.5	586.4	260

Table 1: Summary Statistics. Source: Own illustration, based on data from: See Appendix 1

While the main variables of interest are available for all 20 regions along all 15 years in the analysis, yielding 300 observations, some other variables showed lower availability in the data sources. These missing values have mostly been missing for one particular year, therefore still allowing to estimate with balanced panels in most of the regional analysis. Patents, expressed as the number of applications per regional GDP in PPS, are distributed such that they become less frequent, the further the distribution moves away from zero, with only highly innovative regions in the North coming close to the maximum value. The data on funding sources reveal that private payments have been highest on average, although they also show the largest variation between years and regions. The high standard deviation for all funding sources is also caused by the fact that, in early years of the analysis, some regions had no innovation projects covered by any co-financing, which are therefore leading to some zero observations. The index for institutional quality shows that, while the average is around 0.6, outlying regions can reach values close to one at the top, and close to zero at the bottom of the distribution.

Turning to the outcome variable, Figure 5 shows the distribution of average Patents per GDP in billion PPS in the period under analysis, 2007-2021, for the NUTS 2 regions. The expected pattern of the North performing far better than the South can be recognized clearly.

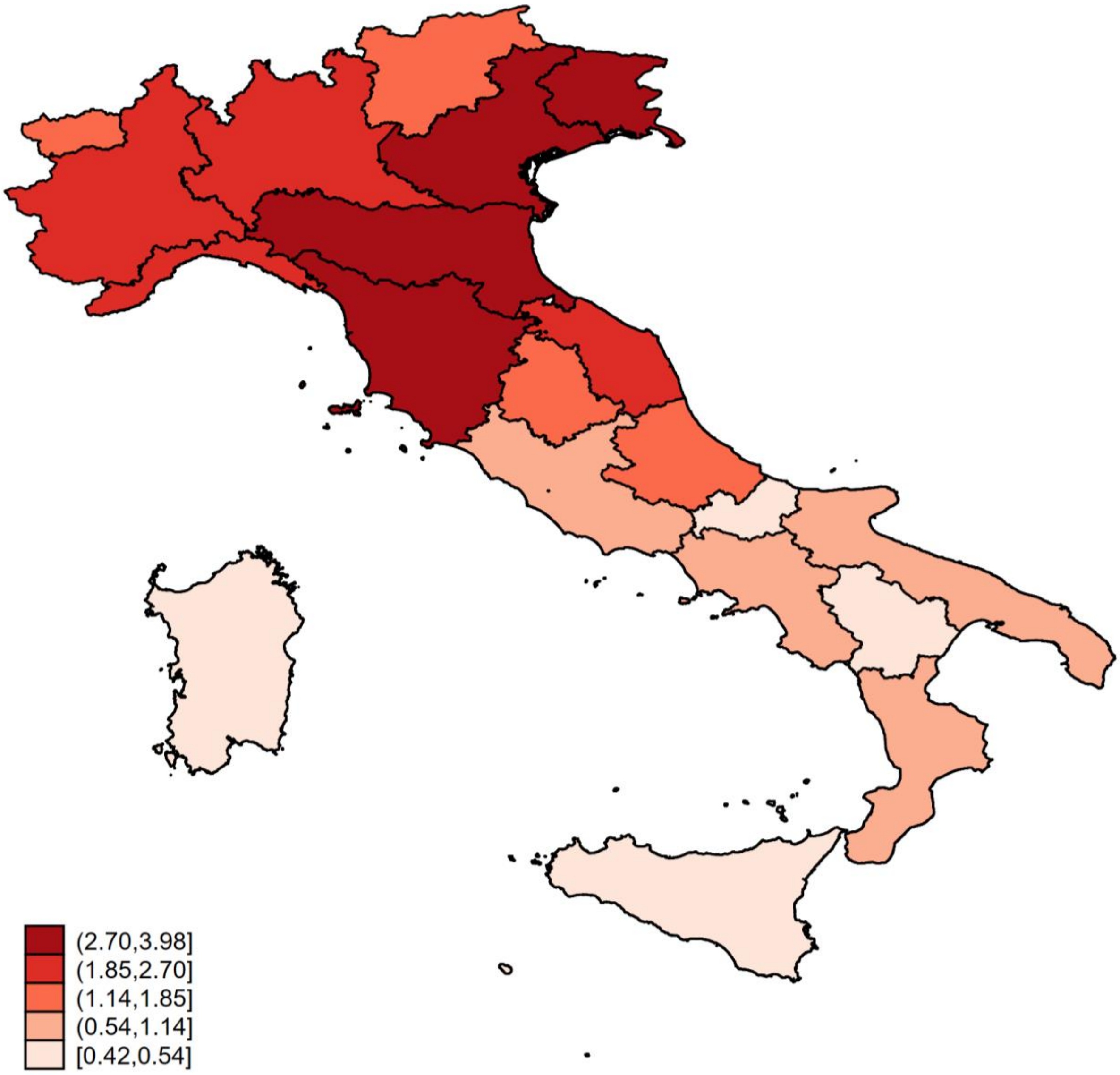

Figure 5: Average patents per GDP in the Italian regions between 2007 and 2021. Notes: Regional GDP has been computed in billion PPS from 2020 in the EU27. Source: Own illustration, based on data from European Commission (2022) and Eurostat (2022)

Looking at the regressor of interest, the data shows that funds are highly correlated, with the association being especially strong between money coming from the EU and money from the state. This is so, as most innovation projects are financed by several sources at the same time, making it difficult to disentangle projects and assign them to only one funding source in the empirical analysis. Regional sources and private money provided by the firms executing the innovation project show the weakest positive association, with a correlation coefficient of only 0.6.

Interesting is also the distribution of funds between the regions. Figure 6 clearly shows that Southern regions receive more funds from all four sources, but the cut between North and South is not as clear as in the case of patents. One reason is the eligibility for EU funding, that defines which regions are eligible to receive co-financing for projects up to a certain share of the total project costs. As this maximum share is higher in the Southern regions, projects in the North must rely on funding sources besides the EU to a larger extent, at least in relative terms of total project costs.

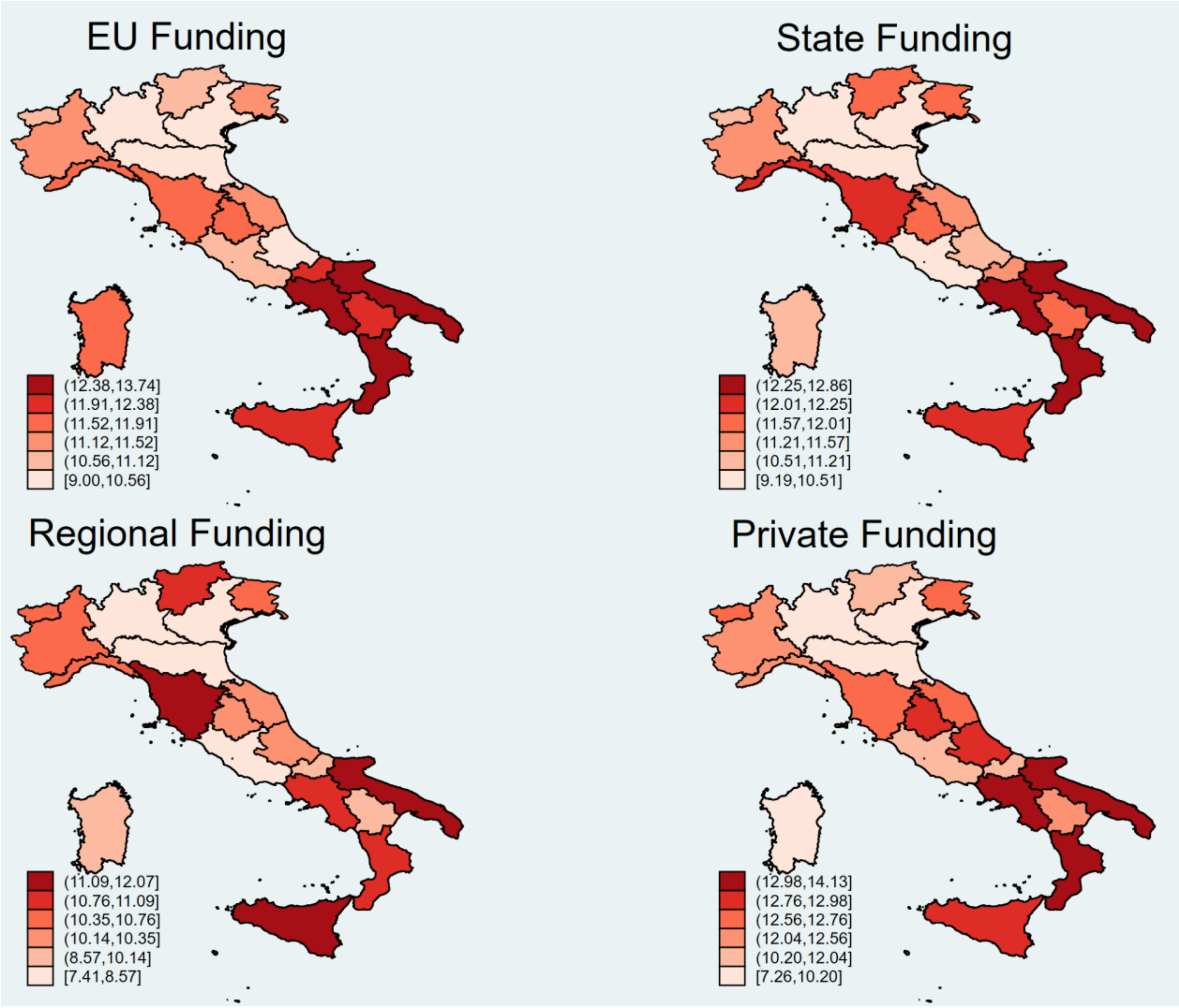

Figure 6: Average funding by sources and region over the analyzed period. Notes: Funding is expressed in logs of Euro per billion regional GDP in PPS. Source: Own illustration, based on data from OpenCoesione (2022c).

When looking at the within-information of patents, so the deviation of patents from the average of each region, there is a slight positive association with the amount of funding received with a one-year lag. Although not causal, this relationship points to regions receiving more money for innovation projects having larger increases in patents. Interestingly, as shown in Figure 7 below, this positive association is stronger for the subset of Northern regions, depicted in the bottom row, compared to the full sample in the upper row in Figure 7. The same association turns out when using a two-year lag of the public funds, while the two-year lag produces even higher coefficients of the funding sources than the one-year lag. This relationship is shown in Appendix 3. Whereas the regression coefficients in Figure 7 are only significant for the state funds, Appendix 3 also leads to positive and significant coefficients of EU funds, but only when restricting the sample to the North. Again, this could be one hint towards higher funding effectivity for innovation in the North, compared to the South.

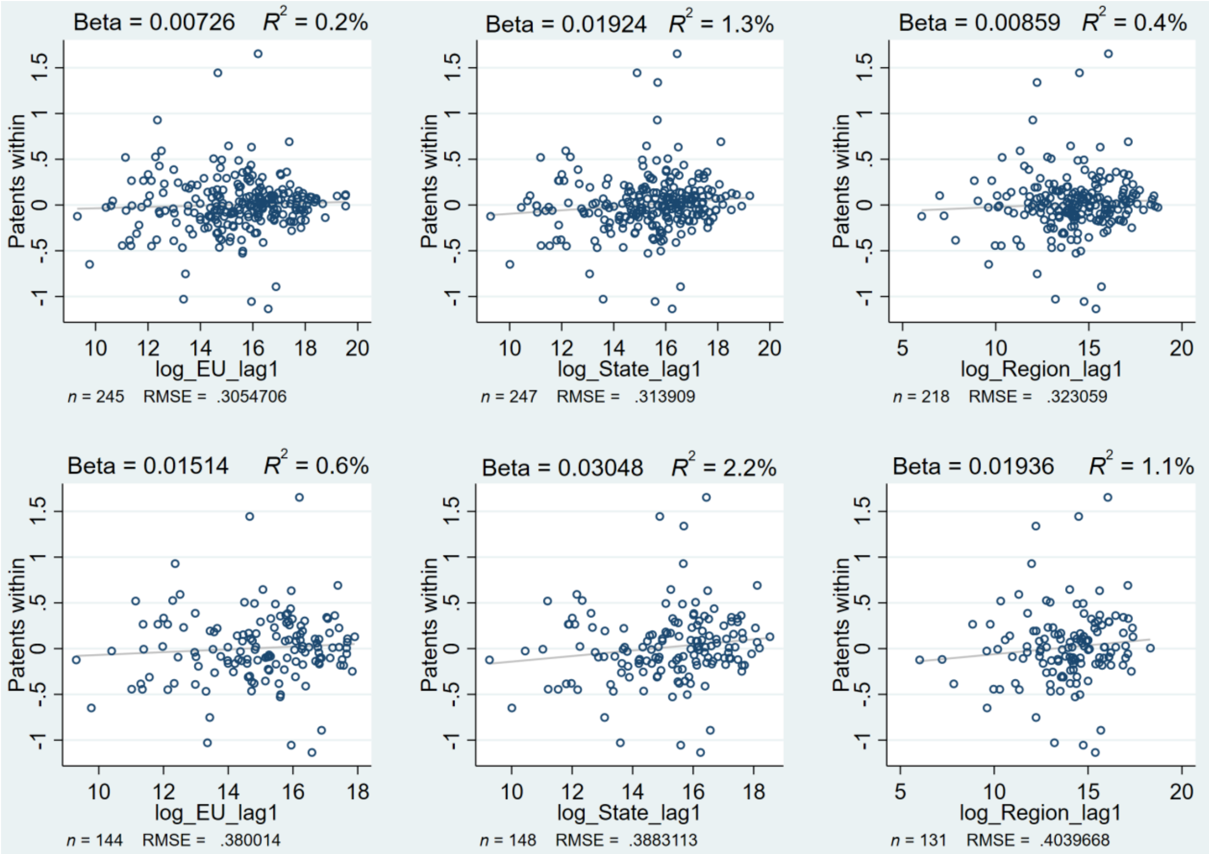

Figure 7: Lagged funding plotted on within-information of patents. Notes: Funding sources are expressed in logs, patents are divided by billion GDP in PPS. "Beta" denotes the regression coefficient of the respective fund. Upper row shows regressions with full sample, bottom row only with Northern regions. Source: Own illustration, based on data from OpenCoesione (2022c) and OECD (2022)

7. Results

The empirical analysis will begin with OLS and estimate Equation 2. All variables are expressed in logs. The IQI and variables in percentage terms have been also included in levels to check for robustness, but results do not differ significantly. With baseline specifications including the 20 Italian regions and 13 years, the number of observations amounts to 260 due to several missing observations in recent years for control variables. This number decreases when introducing longer time lags in the regressions. The regression tables include the within-R-squared for information on the variability of the dependent variable explained by the model. All specifications include region- and year-fixed effects. Robust standard errors are reported in parentheses below the corresponding coefficients.

7.1 Regional Analysis

Table 2 starts with adding controls to the basic specification in column (1), where only the four funding sources, the lagged patents, and three variables reflecting high-skilled labor and research potential are included. These three variables are the share of tertiary educated persons, private R&D expenditures independent of Cohesion policy, and the number of researchers in a region. After the inclusion of unemployment and the employment share in S&T in column (2), and the addition of employment density and IQ in column (3), columns (4) and (5) add GDP p.c., where column (5) does so while excluding possible determinants of GDP p.c. that could cause very high collinearity. This has been done with controls in t-1 predating funding in t, so bad controls should be less of a problem. R&D-expenditures from the government and the tertiary education sector are insignificant in all the specifications, and therefore are not shown here. The share of employment in agriculture is strongly correlated with the share of employment in S&T and is more persistent than the latter variable. As from the regressions, they seem to pick up the same variability, which is why only the employment share in S&T is included in this specification. Specifying funds in t and expecting them to affect change in patents in the same year t might sound far-fetched but is more reasonable when remembering that the year of funding in the dataset indicates the finishing year of projects. Hence, if a project was finished in 2019 and is expected to affect patents in 2019, the project could already have produced innovation outputs during its execution, which is more than a year on average. Specifications with further time lags are presented in the Appendices 4-8, where significance of EU funds, but also of other funds, is rarely obtained. Specifications in the appendix have additionally been attempted to be introduced as in the manner of Rodríguez-Pose and Di Cataldo (2015), with funds and controls being introduced in the same period. Lags of the controls that are larger than one year with respect to the funds turn out insignificant and are therefore not reported.

Dynamic OLS FE regression, with funds in t and controls in t-1

	(1)	(2)	(3)	(4)	(5)
Patents lag1	-0.914***	-0.920***	-0.939***	-0.940***	-0.900***
	(0.0967)	(0.0931)	(0.0894)	(0.0863)	(0.0858)
EU	0.0156**	0.0158**	0.0161**	0.0163**	0.0162**
	(0.00712)	(0.00720)	(0.00708)	(0.00716)	(0.00757)
Region	-0.00469	-0.00422	-0.00465	-0.00494	-0.00197
	(0.00322)	(0.00315)	(0.00326)	(0.00366)	(0.00378)
Private	-0.000380	-0.00131	-0.00139	-0.00139	-0.00237
	(0.00300)	(0.00313)	(0.00330)	(0.00330)	(0.00296)
State	-0.0162**	-0.0156**	-0.0154**	-0.0153**	-0.0168**
	(0.00754)	(0.00723)	(0.00701)	(0.00685)	(0.00746)
IQ			-0.0670	-0.0775	-0.0418
			(0.0922)	(0.114)	(0.122)
Private R&D	0.0258	0.0458	0.0348	0.0297	0.124***
	(0.0419)	(0.0448)	(0.0431)	(0.0362)	(0.0310)
Tertiary	-0.969**	-0.617	-0.516	-0.524	
Education	(0.350)	(0.433)	(0.436)	(0.435)	
Researchers	0.359	0.410*	0.443*	0.438*	
	(0.211)	(0.210)	(0.220)	(0.230)	
Employment		-0.801*	-0.849*	-0.853*	-1.048**
S&T		(0.432)	(0.445)	(0.443)	(0.411)
Unemployment		-0.0986	-0.132	-0.146	
		(0.204)	(0.217)	(0.234)	
Emp.-density			-1.102	-1.058	
			(0.967)	(0.982)	
GDP p.c.				-0.339	-0.470
				(1.075)	(1.132)
Constant	-0.248	-2.412	1.516	4.870	3.135
	(1.919)	(2.631)	(4.442)	(13.36)	(11.38)
Year FE	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES
Observations	260	260	260	260	260
R2-within	0.494	0.500	0.505	0.506	0.483

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Dependent var.: Change in patents per GDP in logs

Only EU- and state funds seem to have a significant influence on patents, while EU funds increase, and state funds seem to decrease innovation. The latter results seem counterintuitive, also as it contradicts the descriptive analysis and the findings from Figure 7 and Appendix 3 for the effect of state funds. A possible explanation are the region-fixed effects picking up the part of the variation in patents that has led to a positive coefficient of state funds in the descriptive analysis. Regional funds are not significant in Table 2 or the Appendices 4-8, while private funds seem to decrease innovativeness in some of the specifications in the Appendix. IQ has been added in the specifications (3) – (5) but is only significant in Appendices 5-7 in the last column. Interestingly, the lagged dependent variable is close to -1 in all specifications, especially in the ones with deeper lags of funds and controls, that tend to show a higher R-squared within (see Appendices 4-8). This points to persistence in patents being very small. In this respect, it might be more appropriate to regress the level of patents in t on the funds and the set of covariates, in the form of a static specification. Regarding controls, private R&D expenditure is significant in column (5) but not in the prior columns, pointing to the variable capturing a similar variation as the control for researchers. Hence, including both controls for innovation potential in the region at the same time might have led to the insignificance in specifications (1) – (4). Remarkably, while private R&D expenditure is often significant, looking at the tables in the appendix leads to the conclusion that it is negatively related to changes in patents. This might be because regions spending a lot of money on R&D already have high levels of patents, leading to smaller changes in patents and possibly reflecting a higher marginal return of R&D spending for regions that show less of such expenses in the private sector. In column (5), GDP p.c. is included, but possible determinants of the variable are excluded. Still, the latter, while being decisive for fund assignment, does not turn out significant. In turn, the employment share in S&T is significant throughout the specifications, while only partly significant in the Appendix.

As mentioned before, patents suffer from several problems as a measure of innovation output, especially because firms in different regions are likely to not rely on patents to protect their property rights to the same extent. Appendices 9-11 present the results of the regressions with deeper time lags and an alternative dependent variable, the change in researchers per GDP in PPS. Although this variable is rather an innovation input than an output, it can still give insights on whether higher funding has led to more researchers being hired, whether by private or public institutions, which is an important driver of innovation. Table 3 shows the estimation outcome with funds in t and controls in t-1.

Dynamic OLS FE regression, with funds in t and controls in t-1					
	(1)	(2)	(3)	(4)	(5)
Researchers lag1	-0.331***	-0.344***	-0.344***	-0.344***	-0.381***
	(0.0696)	(0.0689)	(0.0689)	(0.0665)	(0.0705)
EU	0.00202	0.00214	0.00214	0.00202	0.00238
	(0.00215)	(0.00221)	(0.00221)	(0.00217)	(0.00229)
State	-0.00253	-0.00318	-0.00318	-0.00333	-0.00326
	(0.00188)	(0.00209)	(0.00209)	(0.00212)	(0.00243)
Region	0.00248*	0.00250*	0.00250*	0.00253*	0.00263*
	(0.00121)	(0.00135)	(0.00135)	(0.00143)	(0.00145)
Private	0.000237	0.000715	0.000715	0.000640	0.000409
	(0.00181)	(0.00178)	(0.00178)	(0.00177)	(0.00192)
IQ				-0.0481	-0.0459
				(0.0567)	(0.0552)
Private R&D	0.0717**	0.0657**	0.0657**	0.0645**	0.0680**
	(0.0334)	(0.0314)	(0.0314)	(0.0300)	(0.0286)
Tertiary Education	-0.0606	-0.209	-0.209	-0.255	
	(0.151)	(0.189)	(0.189)	(0.200)	
Employment S&T		0.329	0.329	0.357	0.186
		(0.271)	(0.271)	(0.272)	(0.227)
Unemployment		0.00211	0.00211	0.00338	
		(0.0687)	(0.0687)	(0.0678)	
Emp.-density				0.0333	
				(0.177)	
GDP p.c.					-0.553*
					(0.288)
Constant	1.148**	1.991***	1.991***	1.979*	7.006**
	(0.502)	(0.686)	(0.686)	(0.949)	(3.108)
Year FE	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES
Observations	240	240	240	240	240
R2-within	0.314	0.327	0.327	0.332	0.337

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Dependent var.: Change in researchers per GDP in logs

The lag of researchers is, as opposed to the case of patents, much smaller in magnitude. Hence, the persistence of researchers in the Italian regions is much higher than the persistence in patents. While private R&D can be confirmed to be important, regional funds are, as opposed to the case of patents as dependent variable, significantly explaining the change in researchers. In addition to that, state funds are shown to have a negative impact on changes in researchers when both, funds and controls, are lagged one year (see Appendix 9). Deeper lags lead to no significance of any fund and lead me to the conclusion that EU funds have no significant impact on the number of researchers in a region. IQ is never significant in the specifications with the change in researchers as dependent variable.

Coming back to patents as innovation indicator, the analysis will turn to the inclusion of an interaction term between EU funds and IQ, that will give insights about the relevance of regional institutions for the effectiveness of innovation funds from the EU. Although also the other funding sources could be imagined to be moderated by IQ, this analysis focuses on the EU funds. Before, it is interesting to look at the distribution of IQ between the North and the South. Appendix 12 shows that Southern institutions peak at a value of 0.6 for IQ, whereas the distribution in the North is almost entirely above the value of 0.6. This means that the mean of institutions in the North never includes a Southern region, and vice versa. This makes inference about IQ depending on the location easier. Intuitively, institutions should have an impact on the fund effectiveness with a time lag, as especially the administration and the efficient distribution, which predate the projects' finishing year, can be important for the funding to be effective. Hence, the IQ in t-1 is interacted with EU funds in t.

Table 4 shows the estimation procedure from Table 2 in column (3), except that the interaction term was added. As GDP p.c. is insignificant across specifications, I decided to rather include its likely determinants. Different time lags are considered in the specifications (1) to (5).

Dynamic OLS FE with interaction of EU and IQ

	(1) Funds in t, controls in t-1	(2) All in t-1	(3) Funds in t-1, controls in t-2	(4) All in t-2	(5) Funds in t-2, controls in t-3
Patents lag1	-0.957***	-0.950***	-0.970***	-0.987***	-1.069***
	(0.0905)	(0.101)	(0.0688)	(0.0561)	(0.0856)
EU	0.0117	0.00739	-0.0114	-0.00934	-0.0184
	(0.0137)	(0.0143)	(0.0141)	(0.0136)	(0.0160)
IQ	-0.814	-0.700	-0.412	-0.545	-0.837
	(0.691)	(0.751)	(0.554)	(0.536)	(0.573)
EU#IQ	0.00529	-0.00523	0.00931	0.0184	0.0266
	(0.0168)	(0.0211)	(0.0206)	(0.0179)	(0.0212)
Region	-0.00408	0.00548	0.00134	0.000402	-0.000579
	(0.00330)	(0.00489)	(0.00500)	(0.00386)	(0.00386)
Private	-0.00192	-0.00328	-0.000845	-0.00817**	-0.00974**
	(0.00327)	(0.00264)	(0.00308)	(0.00388)	(0.00430)
State	-0.0157**	-0.00903	0.000756	-0.00394	0.00114
	(0.00735)	(0.00972)	(0.00632)	(0.00818)	(0.00986)
Private R&D	0.0361	0.0378	-0.0715*	-0.0566*	-0.0349
	(0.0413)	(0.0401)	(0.0383)	(0.0272)	(0.0552)
Tertiary Education	-0.661	-0.508	-1.102*	-1.052*	-1.283**
	(0.452)	(0.500)	(0.577)	(0.581)	(0.562)
Researchers	0.425*	0.378	0.0414	0.0809	-0.197
	(0.228)	(0.235)	(0.139)	(0.112)	(0.139)
Employment S&T	-0.764	-0.905*	-0.241	-0.415	0.121
	(0.470)	(0.442)	(0.501)	(0.487)	(0.577)
Unemployment	-0.138	-0.150	-0.116	-0.129	-0.139
	(0.232)	(0.258)	(0.180)	(0.177)	(0.179)
Emp.-density	-0.941	-0.622	-0.935	-0.797	-0.106
	(0.908)	(0.996)	(0.687)	(0.702)	(0.840)
Constant	1.998	0.432	6.998	5.844	6.534
	(4.493)	(5.037)	(4.083)	(4.023)	(4.185)
Year FE	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES
Observations	260	260	260	260	240
R2-within	0.510	0.496	0.593	0.607	0.594

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Dependent var.: Change in Patents per GDP in logs

Although the coefficient of the interaction itself is never significant, which also holds for the coefficients of the funds and IQ themselves, it is important to check the average marginal effects of EU funds at different levels of IQ to gain insights about fund effectiveness. Table 5 shows the average marginal effects of EU funds at the mean of one-year lagged IQ for specification (1) of Table 4. The mean is computed only in Southern regions (1), as the overall mean of IQ (2), and only in Northern regions (3).

Average marginal effects of EU funds at different levels of one-year lagged IQ

EU at:	Marginal effect
(1) IQ = 0.328	0.013 (0.010)
(2) IQ = 0.580	0.015* (0.008)
(3) IQ = 0.748	0.016** (0.008)

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Dynamic OLS FE. Dependent var.: Change in Patents per GDP in logs

Interestingly, the average marginal effects of EU funds are only significant at 5% for the average IQ in the North, which is not included in the distribution of Southern IQ. The overall mean of IQ is significantly connected to stronger effects of EU funds at the 10%-level, although a little smaller in magnitude. For high-quality institutions, the average marginal effect of EU funds on the change in patents can be said to be 1.6 percentage points, meaning that an increase in EU funds by 1% in regions with high-quality institutions is, on average, associated to an increase in patent changes of 1.6 percentage points. Similar magnitudes are obtained when including funds and IQ in t and using deeper lags of the remaining controls.

Although the threat from the Nickell-bias was mentioned in Section 4, there are several reasons why this source of bias can be assumed to be negligible in the case of this analysis. First, the coefficient of the dependent variable yields estimates of around -0.9. The baseline specification can be rewritten in the following way, as in Bun and Kiviet (2003, 146), by adding the lagged dependent variable on both sides of my baseline specification.

$$Patents_{i,t} = \beta_1 * Patents_{i,t-1} + \beta_2 * X_{i,t-k} + \mu_i + \omega_t + \varepsilon_{i,t} \quad (3)$$

Where $X_{i,t-k}$ represents the set of regressors for simplicity. As the estimates for the coefficient ($\beta_1 - 1$) from Equation 2 of the lagged dependent variable are around -0.9, β_1 can be estimated around 0.1, implying a relatively low persistence of patents. This result points to most of the persistence in patents being picked up by the fixed effects and by the controls that have been included in the previous regressions, leaving almost no "true persistence" and making the lagged dependent variable basically irrelevant for the model at the regional level. In fact, testing the coefficients of the lagged dependent variable in Table 4, they are all not statistically significantly different from -1, implying that the omission of the lagged dependent variable would be appropriate in modelling patents. In that case, with the coefficient β_1 in Equation 3 becoming 0, a static model of the following form could be estimated.

$$Patents_{i,t} = \beta_2 * X_{i,t-k} + \mu_i + \omega_t + \varepsilon_{i,t} \tag{4}$$

Estimating the specifications with this equation, as in Table 4, leads to the results presented in Table 6 below.

Static OLS FE with interaction of EU and IQ

	(1) Funds in t, controls in t-1	(2) All in t-1	(3) Funds in t-1, controls in t-2	(4) All in t-2	(5) Funds in t-2, controls in t-3
EU	0.0131	0.00872	-0.0110	-0.00923	-0.0177
	(0.0160)	(0.0130)	(0.0140)	(0.0138)	(0.0163)
IQ	-0.864	-0.780	-0.438	-0.555	-0.804
	(0.675)	(0.787)	(0.567)	(0.521)	(0.565)
EU#IQ	0.00394	-0.00527	0.00943	0.0184	0.0260
	(0.0186)	(0.0208)	(0.0207)	(0.0180)	(0.0214)
Region	-0.00404	0.00525	0.00122	0.000468	-0.000760
	(0.00328)	(0.00477)	(0.00495)	(0.00391)	(0.00360)
Private	-0.00212	-0.00308	-0.000909	-0.00820**	-0.00972**
	(0.00352)	(0.00265)	(0.00309)	(0.00388)	(0.00433)
State	-0.0159*	-0.0103	0.000279	-0.00406	0.00134
	(0.00780)	(0.0108)	(0.00672)	(0.00832)	(0.00956)
Private R&D	0.0383	0.0400	-0.0704*	-0.0561*	-0.0306
	(0.0458)	(0.0431)	(0.0397)	(0.0286)	(0.0501)
Tertiary Education	-0.668	-0.538	-1.122*	-1.059*	-1.212**
	(0.456)	(0.514)	(0.589)	(0.582)	(0.533)
Researchers	0.440*	0.396*	0.0546	0.0859	-0.200
	(0.212)	(0.216)	(0.134)	(0.112)	(0.131)
Employment S&T	-0.783	-0.904*	-0.265	-0.426	0.146
	(0.492)	(0.452)	(0.497)	(0.492)	(0.577)
Unemployment	-0.138	-0.153	-0.120	-0.130	-0.128
	(0.240)	(0.272)	(0.180)	(0.172)	(0.169)
Emp.-density	-0.983	-0.672	-0.964	-0.805	-0.0352
	(0.914)	(1.005)	(0.675)	(0.688)	(0.806)
Constant	2.072	0.619	7.060	5.851	6.045
	(4.574)	(5.206)	(4.150)	(4.044)	(3.832)
Year FE	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES
Observations	260	260	260	260	240
R2-within	0.220	0.197	0.194	0.221	0.214

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Dependent var.: Patents per GDP in logs

Notably, the estimates of all coefficients are very close to the dynamic model. The proximity of estimates, which can be also seen in the results of the estimation of marginal effects of EU funds, suggests that the static model should be the appropriate one, and that a Nickell-bias in the dynamic model should be marginal.

Secondly, the Nickell-bias of the funding sources, that are not persistent and not highly correlated with the lagged dependent variable, should be small. Nevertheless, compared to the simulations in Bun and Kiviet (2003), the number of periods with T=13 is not very high in my case, leaving room for biased estimates. According to simulations of Bun and Kiviet (2003, 148), the downward bias of the coefficient of the lagged dependent variable should be around the range of 1.5 to 3.9 percentage points, while non-persistent regressors as the funding sources, being important also in the static specification, can be assumed to be affected much less, with an upward bias of around 0.1 to 0.2 percentage points.

Until now, the analysis revealed weak evidence about the effectiveness of EU funds for innovation, showing a relatively short-term effect with projects finished in t affecting changes in patents in t. Although issues of reverse causality could be argued to drive these results, this is unlikely as the year of funding only indicates the finishing year of projects, rather than the year in which money was assigned. With an average project duration of more than a year, reverse causality should not be a major issue driving the significance of these results. When turning to the interaction terms, evidence for institutions as moderators of fund effectiveness can be obtained for high-quality institutions only present in the North. This evidence though, only remains significant for the mentioned specification, with funds in t and controls in t-1.

7.2 Provincial Analysis

Within NUTS 2 regions, innovation networks can still be very heterogenous, and the effect of funds on a region's innovation might simply be driven by single, large research centers or "technological districts" that have a certain relevance for innovation in Italy (Caloffi and Bellandi, 2017). Smaller spatial units are more likely to take this heterogeneity into account. In addition, spatial spillovers, that have been shown to be relevant by, e.g., Rodríguez-Pose and Di Cataldo (2015) or Mohl and Hagen (2010), can be tested more reliably with a larger number of small-scale geographical units. Most importantly, using 110 Italian provinces has the advantage of being able to address endogeneity more rigorously, a point that will be mentioned later.

Nevertheless, using smaller units of observation comes with some drawbacks. The time period with data available for estimation reduces to 2007-2013, therefore limiting this part of the analysis to only the first programming period considered in this study. Due to data availability, only a subset of controls compared to the previous step of the analysis can be included for the NUTS 3 regions, with

GDP p.c., tertiary education, IQ, unemployment, employment share in agriculture, average size of firms, and employment density still being available. Importantly, the innovation input of private R&D expenditure and researchers, which were shown to be significant before, are not available. Four of the provinces had to be excluded from the analysis, all of them located on the island Sardinia. These missing observations, and the distribution of patents over the period analyzed can be seen in Figure 8. In the figure, patents are expressed as absolute count variable, while, as in the former part, the empirical analysis will use patents divided by provincial GDP in PPS as dependent variable. Clearly, the North-South divide persists on the provincial level.

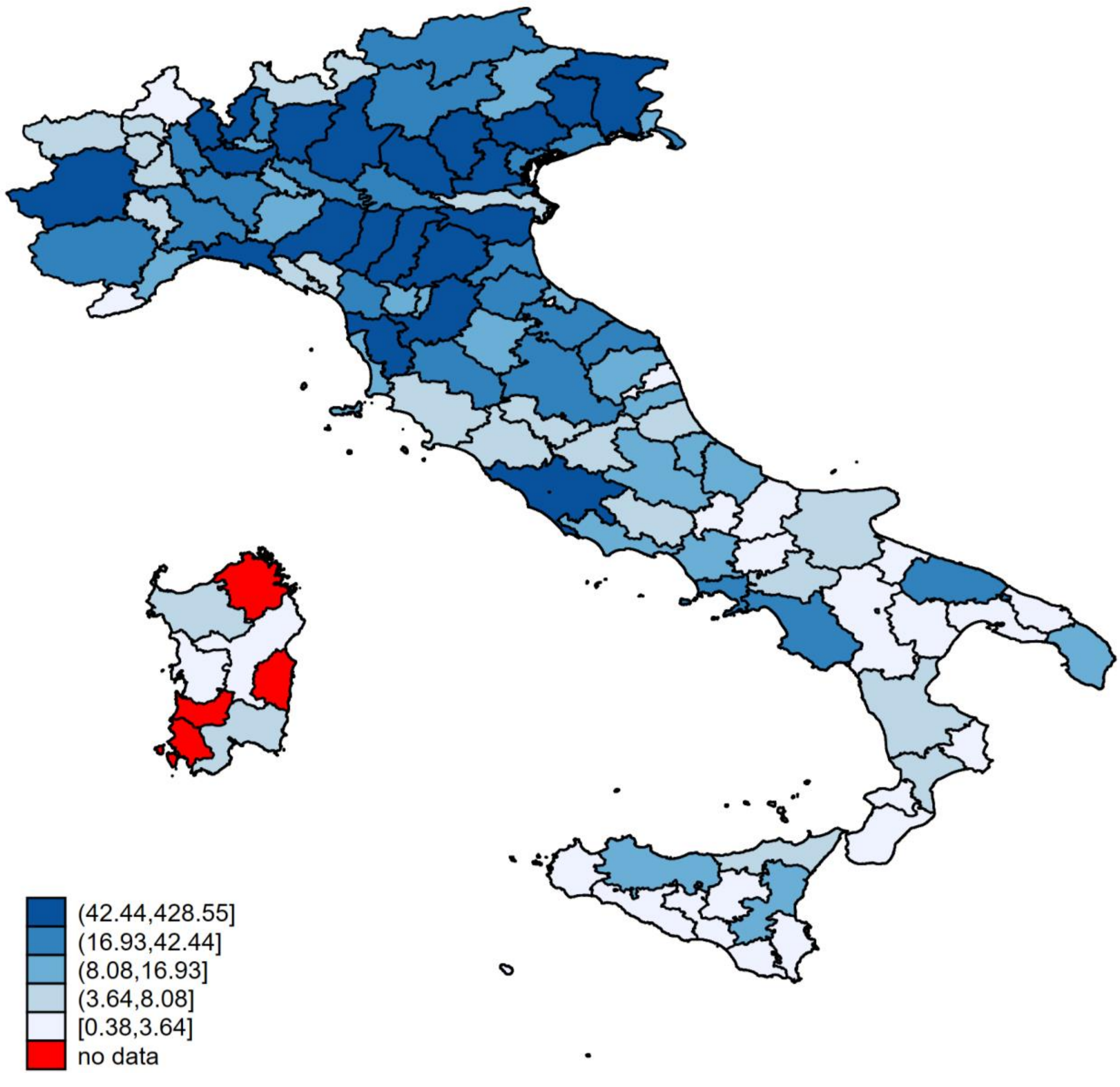

Figure 8: Average patents between 2007-2013 in the Italian provinces. Source: Own illustration, based on data from OECD (2022)

As in the regional part of the analysis, there are some provinces that have received zero funds in some years, so, following the same intuition as before, one will be added to the funding sources. This is done to enable me taking logs of the funding variables. A more serious problem are observations with zeros in the dependent variable at the provincial level. While the baseline model expressed in Equation

2 is a log-linearized one, taking the logs of observations with zero patents would lead to biased estimates. Additionally, it has been shown that estimating log-linearized models with OLS leads to inconsistent estimates under heteroskedasticity of the error term (Santos-Silva and Tenreyro, 2006). Both problems can be tackled with the estimation of a Poisson regression with Maximum Likelihood. In particular, the analysis will proceed with the estimation of a conditional fixed-effect Poisson regression.[2] All the regressors, except for the IQI, are included in logs.

Not considering spatial spillovers and the interaction term, Appendix 13 shows the regression output of the Poisson regressions with the static model, based on Equation 4, and robust standard errors. While only state funds are significant and negative in the first period, the other funding sources do not seem to have a significant impact on patents. IQ is insignificant throughout all five specifications. Tertiary education, employment in agriculture, and employment density are significant in two out of five specifications. While employment in agriculture intuitively reduces patent applications, and a higher employment density leads to more knowledge spillovers and therefore increases patents, the negative sign of the coefficient of tertiary education seems counterintuitive. Nevertheless, part of the positive effect of the qualification level on innovative output might already be captured by provincial fixed effects, also as tertiary education is quite persistent within provinces.

When including the interaction term with IQ and considering spatial spillovers of EU funding, this picture changes. Although the coefficients for IQ and EU funds are insignificant by themselves, Table 7 reports significant interaction terms for specifications (1) and (5). Spatial spillovers have been introduced in the form of a spatial contiguity weight matrix, with first-order neighbors being considered for external effects of funding. The respective coefficients are negative throughout most time lags considered, and significant in columns (3) and (4), counterintuitively pointing towards a province being negatively affected in its innovation potential when neighboring provinces receive more funds. Funds from the state, region, or from private sources are mostly insignificant.

[2] I will use the command „xtpoisson" in Stata to estimate the Poisson model, with patents per GDP as the non-negative count dependent variable

Static Poisson model considering interaction term and spatial spillovers of EU funds

	(1) Funds in t, controls in t-1	(2) Funds in t-1, controls in t-1	(3) Funds in t-1, controls in t-2	(4) Funds in t-2, controls in t-2	(5) Funds in t-2, controls in t-3
EU	-0.0218	0.0103	0.0152	-0.0225	-0.0439
	(0.0190)	(0.0162)	(0.0148)	(0.0267)	(0.0334)
IQ	0.380	0.738	0.892	0.984	0.214
	(0.815)	(0.814)	(0.732)	(0.773)	(0.750)
EU#IQ	0.0458**	0.00828	-0.00157	0.0293	0.0561*
	(0.0215)	(0.0152)	(0.0166)	(0.0259)	(0.0324)
EU spatial lag	0.00591	-0.00714	-0.0143**	-0.0148*	-0.00663
	(0.00775)	(0.00562)	(0.00703)	(0.00826)	(0.00863)
State	-0.0188**	-0.0104	-0.0108	0.00187	0.000643
	(0.00951)	(0.0101)	(0.00780)	(0.0102)	(0.0118)
Region	-0.00285	-0.00325	-0.00156	-0.0104	-0.00559
	(0.00495)	(0.00519)	(0.00623)	(0.00716)	(0.00773)
Private	0.00192	0.00231	0.000430	0.00547	0.00275
	(0.00398)	(0.00382)	(0.00409)	(0.00401)	(0.00474)
Tertiary Education	0.0693	0.0442	-1.996***	-2.253***	-0.239
	(0.490)	(0.472)	(0.698)	(0.720)	(0.919)
Unemp.	0.0420	0.0475	0.148	0.0956	-0.0488
	(0.106)	(0.103)	(0.139)	(0.125)	(0.142)
Employment Agriculture	-0.339	-0.352*	-0.116	-0.0797	-0.173
	(0.207)	(0.206)	(0.222)	(0.199)	(0.292)
Emp.-density	0.261	0.225	0.265	0.276	-0.0300
	(0.304)	(0.286)	(0.242)	(0.249)	(0.359)
Firmsize	-0.419	-0.359	-0.164	-0.133	-0.849**
	(0.297)	(0.292)	(0.287)	(0.292)	(0.382)
Year FE	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES
Observations	624	624	519	519	408

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Dependent var.: Patents per GDP

To estimate the impact that the quality of institutions has on the funds' effectiveness, it makes sense to examine the distribution of the IQ-variable first, as it has been done for the regional part. Appendix 14 shows the histograms of the IQ in the Northern and Southern provinces, marking a cut around the index value of 0.6 that few Southern regions surpass in the period of analysis. For this reason, significant marginal effects at values for the IQI above 0.6 would indicate that only Northern institutions amplify the funds' effectiveness. Looking at the marginal effects of the five specifications, only the ones for specification (3) turn out significant. They are presented in Table 8 below.

Average marginal effects of EU funds in t-1 at different levels of two-year lagged IQ

EU lag1 at:	Marginal effect
(1) IQ = 0.285	0.015
	(0.010)
(2) IQ = 0.570	0.014
	(0.008)
(3) IQ = 0.723	0.014*
	(0.008)

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Static Poisson model: Average marginal effect of EU funds in t-1 at different IQ-values.

Again, the IQ-values have been chosen to be, as before, at the average values of the Southern provinces (1), the overall sample (2), and the Northern provinces (3). However, minor deviations from the average values have been checked not to lead to different results. Remarkably, marginal effects are of very similar magnitude as obtained in the regional analysis, even though they were obtained with different time lags. Still, only for high-quality institutions exclusively present in the North, EU funds are increasing patenting at a 10% significance level.

Although the previous approach is useful to correct for heteroskedasticity and treat zeros in the patent data, another problem remains. While lagged values of the regressors have been preferred in the previous specifications, this might be not sufficient to prevent reverse causality from biasing the estimates if there is persistence in the regressors. Reverse causality is a problem that has been mentioned also in the analysis by Rodríguez-Pose and Di Cataldo (2015). Regions that are more innovative might simply receive more funds as there are more options for co-financing to be allocated to innovative projects, constituting the reverse relationship of the two main variables. If such issues are in place, it is especially important to control for the endogeneity of funds, as they provide the coefficient of interest. In addition, there may be a problem of unobserved variables affecting both, patenting, and the amount of funds a province received. If these factors are varying over time and are heterogenous across provinces, fixed effects will not absorb them and they will bias the estimation (Mohl and Hagen, 2008, 3).

With an IV-approach, these problems can be tackled. As instruments are often hard to find, Blundell and Bond (1998) propose using internal instruments in the form of lagged levels and first differences of the regressors. The implementation of this "System-GMM"-approach[3] is described in more detail by Roodman (2009). He describes the appropriateness of the technique for datasets with many cross-section units and few time periods, as in the NUTS 3 analysis here, where there are three types of regressors: Strictly exogenous, predetermined but not strictly exogenous, and endogenous regressors. The alternative estimation method of first-differenced GMM was shown by the author to lead to a weak instruments problem if the dependent variable is relatively random and fluctuates over time. As the patents used in my analysis are fluctuant and have little persistence over time, I will use the System-GMM estimator. In this context, first differences instead of orthogonal deviations are applied, as there are no gaps in the dataset used here. To not encounter problems due to heteroskedasticity, I will use the two-step estimation with Windmeijer-corrected standard errors, that correct for a possible downward bias of the errors in the two-step estimation (Roodman, 2009).

Problematically, estimating with System-GMM does not allow me to correct for the zeros in the dependent variable with a Poisson model approach. Therefore, I run estimations with the full sample from which observations with zeros in patents have been transformed to missing values when taking logs. Although this can bias the estimations, the relatively small number of zeros, compared to the sample size, should keep results in a credible range. Additionally, to avoid possible proliferation of instruments that would lead to overidentification, I collapse the set of instruments used in the estimation. Nevertheless, proliferation should be more of an issue in the setting of few cross-section units and many time periods, which is the opposite of what is available for the NUTS 3-level analysis here (Labra and Torrecillas, 2018).

For the System-GMM estimations, I will first consider funds as endogenous in the period t, and controls in t-1. As in Mohl and Hagen (2010), not just the funds but also all the other regressors are considered as endogenous. This specification has also been chosen because instrument exogeneity was not always satisfied in the analysis in the case of including some controls as exogenous, or even predetermined and not strictly exogenous. Patents are, in contrast to the former part, not transformed by the division through provincial GDP, as this has led to problems with autocorrelation in several specifications. To still consider GDP as possibly important confounder of the effect, I will include it in per capita-terms as control in specification (5). Table 9 shows the output of the regressions with both, the lagged dependent variable and the dependent variable in logs. Funds do not have a significant impact on patents, while lagged patents are significantly affecting the outcome variable in the first three specifications. IQ, included as regressor in t-1 for specifications (4) and (5), does not yield significant estimates. Spatial spillovers of EU funds are, as expected, positive and significant in almost all specifications.

[3] The System-GMM will be estimated with the command "xtabond2" in Stata

System-GMM estimations with endogenous funds in t, and controls in t-1					
	(1)	(2)	(3)	(4)	(5)
Patents lag1	0.546***	0.438***	0.475**	0.306	0.133
	(0.206)	(0.162)	(0.215)	(0.215)	(0.202)
EU	-0.148	-0.0695	-0.0332	-0.0498	-0.0226
	(0.131)	(0.0479)	(0.0544)	(0.0620)	(0.0537)
State	0.0699	0.0157	-0.0111	-0.000693	-0.0155
	(0.110)	(0.0496)	(0.0587)	(0.0613)	(0.0534)
Region	0.0255	0.00270	0.0281	-0.0154	-0.0102
	(0.0413)	(0.0253)	(0.0259)	(0.0184)	(0.0188)
Private	-0.0260	0.00841	-0.0113	0.0221	0.0183
	(0.0207)	(0.0163)	(0.0273)	(0.0200)	(0.0199)
IQ				0.353	0.326
				(0.290)	(0.260)
EU spatial lag	0.115**	0.0855***	0.0526	0.0828**	0.0711**
	(0.0457)	(0.0329)	(0.0357)	(0.0390)	(0.0292)
Tertiary Education	0.542 (2.255)	-0.586 (1.642)	0.233 (1.600)	-0.887 (1.262)	-1.809 (1.241)
Unemployment		-1.335***	-0.399	-0.321	0.151
		(0.466)	(0.412)	(0.410)	(0.463)
Employment Agriculture			-0.824 (0.672)	-0.756 (0.633)	-0.170 (0.597)
Emp.-density			-0.629	0.271	0.679
			(0.729)	(0.595)	(0.587)
Firm size				-1.072	-1.610*
				(0.983)	(0.934)
GDP p.c.					3.197***
					(1.199)
Constant	-0.274	5.578	-2.790	7.625	-17.52
	(6.341)	(5.024)	(6.203)	(5.091)	(10.91)
Year FE	YES	YES	YES	YES	YES
Observations	598	595	595	591	591
P-value Hansen-test	0.171	0.163	0.112	0.139	0.275
P-value AR(1)-test	0.002	0.001	0.004	0.006	0.021
P-value AR(2)-test	0.414	0.452	0.400	0.628	0.944

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9: System-GMM estimations with dependent var.: Patents in logs

In addition to the time lags chosen in Table 9, Appendix 15 shows the estimation results with funds in t-1 and controls in t-2, while patents are kept in logs and all regressors are treated as endogenous. Most of the estimates seem to confirm lagged patents to be significant around a value of 0.5, while state funds seem to have a negative, and private funds a positive effect on innovation. Significant EU funds are only confirmed at the 10%-level for specification (1). Positive and significant spatial spillovers are found mostly also for these time lags considered, while coefficients of IQ, again, are insignificant. The consistently positive coefficients for spatial spillovers in this part stand in contrast to the negative estimates obtained with the Poisson model.

Then, when adding the interaction term of IQ and EU funds, IQ has, just as the other controls, been lagged one period with respect to the funds. This has been done based on the evidence that, again, especially the capacity of regional institutions to influence fund assignment and distribution matters in making funds ineffective. As these processes take place before the finishing year of projects, and projects take around one year on average, lagging IQ one year with respect to the funds should appropriately match the point in time where the respective funds were managed, assigned, and distributed by managing authorities. Table 10 shows the System-GMM estimations with all regressors being endogenous, funds included in t, and controls as described above in t-1.

System-GMM estimations with endogenous funds in t, controls in t-1, and interaction term

	(1)	(2)	(3)	(4)	(5)
Patents lag1	0.395^{**}	0.448^{**}	0.469^{***}	0.362^{**}	0.295^{*}
	(0.197)	(0.178)	(0.165)	(0.180)	(0.155)
EU	-0.0316	-0.0574	-0.0432	-0.0417	-0.0238
	(0.0459)	(0.0444)	(0.0499)	(0.0426)	(0.0469)
IQ	1.936	0.548	0.996	2.314^{*}	1.662
	(1.196)	(1.235)	(1.569)	(1.313)	(1.498)
EU#IQ	0.0384	0.113	0.0783	0.0816	0.0437
	(0.120)	(0.0800)	(0.0917)	(0.0801)	(0.0666)
State	-0.0193	-0.0314	-0.0306	-0.0415	-0.0298
	(0.0622)	(0.0512)	(0.0637)	(0.0545)	(0.0558)
Region	0.0243	0.0159	0.0103	-0.00540	0.00344
	(0.0215)	(0.0215)	(0.0214)	(0.0261)	(0.0214)
Private	-0.0185	-0.00969	-0.0121	-0.00225	-0.0115
	(0.0136)	(0.0151)	(0.0191)	(0.0212)	(0.0174)
EU spatial lag	0.0466	0.0414^{*}	0.0376	0.0555^{**}	0.0437^{*}
	(0.0368)	(0.0246)	(0.0245)	(0.0281)	(0.0257)
Tertiary Education	0.509	-0.264	-0.771	-2.653^{*}	-2.640^{*}
	(1.541)	(1.287)	(1.470)	(1.574)	(1.356)
Unemployment		-0.688^{*}	-0.367	-0.00843	0.332
		(0.359)	(0.418)	(0.415)	(0.337)
Employment Agriculture			-0.313	-0.516	-0.241
			(0.476)	(0.458)	(0.420)
Emp.-density			-0.348	-0.00569	-0.0776
			(0.588)	(0.512)	(0.507)
Firm size				-2.157^{***}	-1.791^{*}
				(0.801)	(1.044)
GDP p.c.					2.521^{**}
					(1.268)
Constant	-0.947	3.130	1.787	14.91^{**}	-11.55
	(4.138)	(3.353)	(5.640)	(6.563)	(16.76)
Year FE	YES	YES	YES	YES	YES
Observations	596	595	595	593	593
P-value Hansen-test	0.275	0.321	0.255	0.289	0.431
P-value AR(1)-test	0.004	0.002	0.002	0.004	0.004
P-value AR(2)-test	0.540	0.545	0.519	0.985	0.934

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 10: System-GMM estimations with interaction term and dependent var.: Patents in logs

Although IQ is positive and significant in specification (4), the funding sources and the interaction term are insignificant in all cases. While the magnitude of lagged patents becomes slightly lower in this specification, spatial spillovers remain positive. GDP p.c., tertiary education, and firm size are found to be significantly affecting patenting, where the latter factor's importance is confirmed in Appendix 16 showing the same estimations for funds in t-1 and controls in t-2. For these alternative time lags, lagged patents are again around the value of 0.5. EU funds turn out insignificant, but IQ is significant in the first two, and the interaction term significant in the first four specifications. Regional and private funds are significant in the last two specifications of Appendix 16 and are, respectively, negatively and positively affecting patents. The regression in column (2) in the Appendix casts some doubts about the exogeneity of instruments based on the Hansen test as, although only in this case, the null hypothesis of instruments being exogenous must be rejected at the 10% significance level. Positive spatial spillovers are confirmed in the estimation, just as a negative effect of firm size. Although the interactions become significant in this alternative specification, they are negative, and when marginal effects are checked, they are still insignificant for different IQ-levels, which is also true for the estimations in Table 10.

8. Discussion

As mentioned in Ciani and de Blasio (2015), it is likely that effects taking place within one geographical unit and being not constant over time are omitted in the specification used here, as the number of controls is limited by the available data. E.g., if a province has been particularly affected by the crisis in one of the years under analysis, its patents might have gone down as less money was available for spendings on R&D, in the firms and at the public level. This decrease in patents would then not be associated to the fixed effects or any of the controls but would be captured by the error term, also as the private R&D expenditures are not available for the NUTS 3-level. If a province's propensity to be affected by the crisis and its propensity to receive funds are correlated, which is likely the case, then estimates would be biased downwards, as decreases in patents would be mistakenly associated to the funding. Another way in which OVB can bias results is because of factors that determine how treatment is assigned, and that are, at the same time, correlated with the innovation outcome. On the other hand, and in favor of this analysis, it can be said that the set of controls already included, such as the unemployment rate and regional GDP p.c., already are factors commonly considered on a political level for fund assignment. As an example, this is reflected by the assignment rules for EU Structural Funds based on the regional GDP p.c. as percentage of the EU average. Additionally, the analysis by Coppola et. al (2020, 92) that also focuses on the impact of Structural Funds in the Italian regions does not find significance for the determinants of fund allocation for the funds' effectiveness, potentially dampening the bias from OVB here.

Furthermore, patents can be criticized as an innovation indicator. Although researchers were used as alternative dependent variable, it would have been interesting to use a citation-weighted patent count if the data were available for the spatial units analyzed. Such an approach has been chosen in Capello and Lenzi (2013). It should be borne in mind that patents are simply one indicator to measure innovation output. Surely, the mentioned categories are often triggering other innovation outputs that are not necessarily protected with patents and would therefore not be captured by the analysis.

Clearly, having data on the firm-level would have been preferred over region-data. This is so as the characteristics of firms are decisive to determine whether funds are transformed to actual innovative output, in addition to characteristics of regions. An analysis as in Bertamino et al. (2016), where the location of firms in a region, but also the firm's activity in a certain sector and their profitability is included, would have been preferred over a regional analysis. On a regional scale, there also might be an issue of innovative firms self-selecting to regions in the North, where infrastructure and conditions for generating patents are better.

For the provincial analysis, one serious limitation is that no information on private R&D expenditure independent of Cohesion Policy, and no data on the number of researchers is available. In the NUTS 2 analysis, these variables have been shown to be significant inputs for the innovation process. More importantly, private R&D expenditures capture the variation in patents due to investments that were made independent of Cohesion Policy. Not considering these investments could be one explanation for the lack of significance for the funds' coefficients in most NUTS 3 regressions. Similarly, not being able to address endogeneity and appropriately deal with zeros in the dependent variable at the same time is an issue casting doubts about the results presented.

9. Conclusions

This analysis has dealt with the effect of EU funds for the promotion of research and innovation in the Italian regions and provinces. To do so, several empirical specifications have been set up, controlling for endogeneity of various forms, and considering multiple time lags with which the funds could possibly affect patenting. The regional analysis has provided evidence of institutions mattering for funds to positively affect innovation. Nevertheless, this has only been found with funds included in year t for the dynamic OLS FE analysis, and with funds included in t-1 for the static Poisson estimation in the provincial analysis. Magnitudes of the marginal effects of EU funds at different IQ-levels with OLS were confirmed by the provincial analysis with the static Poisson estimation, although at a lower significance level. Doubts about the IQ as a moderator of the effect come from other time lags included, which turn the marginal effect of EU funds insignificant. This also must be concluded when addressing endogeneity with the System-GMM approach. Aside from the IQ as moderating factor, EU funds themselves rarely turn out significant in the different estimation techniques, raising doubts about the effectiveness of these funds.

Overall, there is weak evidence of EU funds having a positive impact on patents as innovation output. Although Table 5 indicates that this relation is significant for funds included in the same period as patents, and controls lagged by 1 year, deviating from these chosen time lags makes funds insignificant in the clear majority of cases. This is also the case when choosing an alternative dependent variable, namely the number of researchers in a region. Regarding the influence of IQ on the effectiveness of EU funds, it can be said that there is weak evidence for high-quality institutions being positively associated to higher fund effectiveness, although this result is also obtained rarely and not significant in most time lags considered. In these few cases, an increase in EU funds of 1% leads to an increase in patents changes of around 1.6 percentage points, if the region/province is equipped with high-quality institutions.

Despite the limitations presented in the previous section, this analysis shows a variety of estimation techniques with several benefits and drawbacks, and with almost all of them pointing into the same direction of no significance of EU funds for patenting. As patents as a measure for innovation were aimed to be used as a tool for cohesion by the European Commission, this evidence has high importance for Italy, as funds in all regions and provinces seem to not have had the desired impact. Although initially hypothesized, this impact does not seem to be more positive for Northern areas due to their higher IQ. The evidence presented here leads to the conclusion that rethinking the massive spendings of EU Cohesion Policy for innovation support is necessary to allow convergence reducing the gap between North and South in Italy.

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Appendix

Appendix 1: Categories of spending promoting innovation

1. RTD assistance, in particular in SMEs (including access to RTD services in research centers)
2. Assistance to SMEs in the promotion of ecological products and production processes
3. Other measures to stimulate research, innovation, and entrepreneurship in SMEs
4. RTD activities in research centers
5. Research and innovation activities in public research centers and centers of competence, including networking
6. Research and innovation activities in private research centers, including networking
7. Research and innovation infrastructures (public)
8. RTD infrastructures and centers of expertise in a specific technology
9. Investments in infrastructure, capacity and equipment in large companies directly linked to research and innovation activities
10. Investments in infrastructure, capacity and equipment in SMEs directly linked to research and innovation activities
11. Investments in enterprises directly related to research and innovation
12. Generic productive investment in small and medium-sized enterprises ("SMEs")
13. Research and innovation processes in large companies
14. Research and innovation processes in SMEs (including voucher schemes, process, design, service, and social innovation)
15. Support for clusters and business networks, mainly for the benefit of SMEs
16. Technology transfer and cooperation between universities and businesses, mainly for the benefit of SMEs
17. Technology transfer and improvement of cooperation networks

Appendix 2: Variable description and sources

Patents: Patents per billion GDP in PPS from 2020 in the EU27. Data on patents from: European Commission (2022) & Eurostat (2022) for NUTS 2, OECD (2022) for NUTS 3; GDP in PPS from 2020: Eurostat (2022b)

EU-, State-, Region-, and Private-Funds: Funds per billion GDP in PPS from 2020 in the EU27. Fund-data: OpenCoesione (2022c). GDP in PPS from 2020: Eurostat (2022b)

Institutional Quality Index (IQI) between 0 and 1: Nifo and Vecchione (2015)

Employment density: Number of employees aged 15-64 in a region, divided by the area of that region. Number of employees: Eurostat (2022c). Area of region: Eurostat (2022d)

Unemployment rate: Unemployed aged 15-74, percentage. Eurostat (2022a)

Population (in thousands). Eurostat (2022e)

Population from 25-64 years with tertiary education (%). Eurostat (2022f)

Researchers (Full-time equivalents from all sectors). Eurostat (2022g)

Employment share in agriculture: Number of people employed in Agriculture, forestry and fishing divided by total employment in region. OECD (2022a).

Employment share in Science and Technology: Number of people employed in S&T divided by total employment in region. Eurostat (2022h)

GDP per capita (in Euro): Eurostat (2022i)

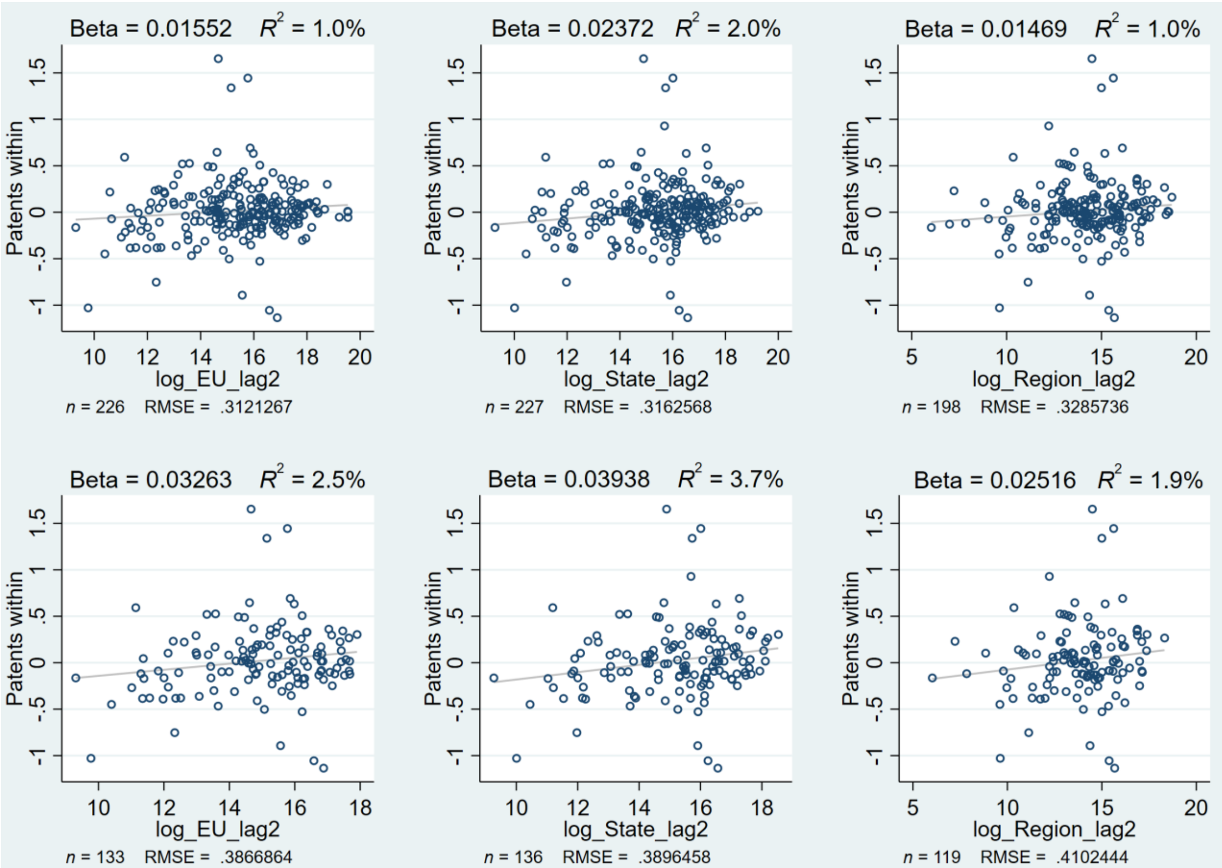
Firmsize: Number of employees (15-64 years old) divided by number of firms. Number of employees (age 15-64): Eurostat (2022c); Number of firms: ISTAT (2022)

Gross Expenditure on R&D by private sector (Euro per inhabitant): Eurostat (2022j)

Gross Expenditure on R&D by government sector (Euro per inhabitant): Eurostat (2022j)

Gross Expenditure on R&D by tertiary education sector (Euro per inhabitant): Eurostat (2022j)

Appendix 3: Two-period lagged funding plotted on within-information of patents



Appendix 3: Notes: Funding sources are expressed in logs, patents are divided by billion GDP in PPS. “Beta” denotes the regression coefficient of the respective fund. Upper row shows regressions with full sample, bottom row only with Northern regions. Source: Own illustration, based on data from OpenCoesione (2022c) and OECD (2022)

Appendix 4: Dynamic OLS FE: Funds and controls lagged one period

	(1)	(2)	(3)	(4)	(5)
Patents lag1	-0.909***	-0.912***	-0.926***	-0.927***	-0.888***
	(0.106)	(0.101)	(0.0985)	(0.0967)	(0.0971)
EU	0.00370	0.00374	0.00400	0.00399	0.00311
	(0.00930)	(0.0102)	(0.00994)	(0.00990)	(0.00898)
Region	0.00466	0.00583	0.00510	0.00508	0.00805
	(0.00575)	(0.00530)	(0.00535)	(0.00528)	(0.00509)
Private	-0.00149	-0.00355	-0.00342	-0.00343	-0.00410**
	(0.00230)	(0.00220)	(0.00221)	(0.00223)	(0.00172)
State	-0.00983	-0.00857	-0.00772	-0.00770	-0.00885
	(0.0113)	(0.0119)	(0.0114)	(0.0110)	(0.00996)
IQ			-0.0513	-0.0519	-0.0266
			(0.0992)	(0.117)	(0.122)
Private R&D	0.0247	0.0480	0.0376	0.0372	0.114***
	(0.0356)	(0.0367)	(0.0403)	(0.0403)	(0.0265)
Tertiary Education	-0.855**	-0.431	-0.358	-0.358	
	(0.357)	(0.462)	(0.484)	(0.492)	
Researchers	0.304	0.365*	0.392*	0.392	
	(0.211)	(0.211)	(0.224)	(0.232)	
Employment S&T		-0.925**	-0.960**	-0.960**	-1.062***
		(0.415)	(0.436)	(0.434)	(0.333)
Unemployment		-0.157	-0.182	-0.183	
		(0.219)	(0.227)	(0.245)	
Emp.-density			-0.870	-0.868	
			(1.059)	(1.067)	
GDP p.c.				-0.0220	-0.0675
				(0.974)	(0.974)
Constant	-0.127	-2.613	0.502	0.721	-0.933
	(1.978)	(2.782)	(4.819)	(12.44)	(9.789)
Year FE	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES
Observations	260	260	260	260	260
R2-within	0.480	0.487	0.490	0.490	0.474

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix 4: Dep. Var.: Change in patents per GDP in logs

Appendix 5: Dynamic OLS FE: Funds lagged one, controls lagged two periods

	(1)	(2)	(3)	(4)	(5)
Patents lag1	-0.952***	-0.956***	-0.962***	-0.963***	-0.934***
	(0.0644)	(0.0656)	(0.0686)	(0.0690)	(0.0655)
EU	-0.00474	-0.00465	-0.00415	-0.00410	-0.00365
	(0.00503)	(0.00514)	(0.00540)	(0.00537)	(0.00533)
Region	0.00151	0.00175	0.00145	0.00132	0.00374
	(0.00529)	(0.00510)	(0.00520)	(0.00536)	(0.00470)
Private	-0.000259	-0.000555	-0.000229	-0.000225	-0.00150
	(0.00275)	(0.00291)	(0.00280)	(0.00280)	(0.00183)
State	0.0000570	0.0000859	0.000733	0.000780	0.000280
	(0.00722)	(0.00694)	(0.00713)	(0.00711)	(0.00703)
IQ			0.114	0.109	0.180**
			(0.0901)	(0.0983)	(0.0701)
Private R&D	-0.0674*	-0.0602	-0.0680*	-0.0703*	-0.0254
	(0.0326)	(0.0360)	(0.0348)	(0.0373)	(0.0424)
Tertiary	-1.240**	-1.132*	-0.892	-0.895	
Education	(0.471)	(0.586)	(0.574)	(0.579)	
Researchers	-0.000724	0.0195	0.0579	0.0559	
	(0.133)	(0.150)	(0.148)	(0.149)	
Employment		-0.249	-0.362	-0.364	-0.965**
S&T		(0.480)	(0.484)	(0.478)	(0.391)
Unemployment		-0.0650	-0.106	-0.113	
		(0.166)	(0.174)	(0.179)	
Emp.-density			-0.993	-0.973	
			(0.770)	(0.784)	
GDP p.c.				-0.152	-0.182
				(0.696)	(0.844)
Constant	3.739**	3.091	6.227	7.734	1.187
	(1.632)	(2.553)	(4.242)	(9.057)	(8.520)
Year FE	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES
Observations	260	260	260	260	260
R2-within	0.588	0.588	0.594	0.594	0.576

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix 5: Dep. Var.: Change in patents per GDP in logs

Appendix 6: Dynamic OLS FE: Funds and controls lagged two periods

	(1)	(2)	(3)	(4)	(5)
Patents lag1	-0.970***	-0.978***	-0.981***	-0.981***	-0.959***
	(0.0518)	(0.0532)	(0.0574)	(0.0572)	(0.0547)
EU	0.00391	0.00390	0.00406	0.00401	0.00383
	(0.00458)	(0.00471)	(0.00505)	(0.00513)	(0.00495)
Region	0.000948	0.00143	0.00110	0.000981	0.00354
	(0.00407)	(0.00380)	(0.00374)	(0.00390)	(0.00372)
Private	-0.00664*	-0.00773*	-0.00761*	-0.00762*	-0.00958**
	(0.00377)	(0.00376)	(0.00391)	(0.00392)	(0.00445)
State	-0.00685	-0.00614	-0.00470	-0.00453	-0.00467
	(0.00872)	(0.00815)	(0.00862)	(0.00865)	(0.00835)
IQ			0.0879	0.0833	0.144*
			(0.0981)	(0.106)	(0.0693)
Private R&D	-0.0578**	-0.0465*	-0.0528**	-0.0553*	-0.00695
	(0.0240)	(0.0240)	(0.0229)	(0.0278)	(0.0317)
Tertiary Education	-1.232***	-1.020*	-0.829	-0.832	
	(0.394)	(0.513)	(0.545)	(0.547)	
Researchers	0.0349	0.0658	0.0933	0.0913	
	(0.123)	(0.125)	(0.121)	(0.121)	
Employment S&T		-0.482	-0.573	-0.575	-1.142***
		(0.432)	(0.454)	(0.448)	(0.353)
Unemployment		-0.0470	-0.0822	-0.0888	
		(0.181)	(0.193)	(0.193)	
Emp.-density			-0.781	-0.762	
			(0.747)	(0.769)	
GDP p.c.				-0.155	-0.194
				(0.683)	(0.809)
Constant	3.406**	2.086	4.568	6.104	1.004
	(1.378)	(2.087)	(3.739)	(8.363)	(8.143)
Year FE	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES
Observations	260	260	260	260	260
R2-within	0.600	0.602	0.605	0.605	0.591

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix 6: Dep. Var.: Change in patents per GDP in logs

Appendix 7: Dynamic OLS FE: Funds lagged two, controls lagged three periods

	(1)	(2)	(3)	(4)	(5)
Patents lag1	-1.060***	-1.061***	-1.065***	-1.065***	-1.035***
	(0.0809)	(0.0841)	(0.0828)	(0.0824)	(0.0787)
EU	0.00189	0.00179	0.00197	0.00193	0.00232
	(0.00528)	(0.00534)	(0.00543)	(0.00533)	(0.00457)
Region	-0.000431	-0.000153	-0.000232	-0.0000956	0.000984
	(0.00429)	(0.00403)	(0.00398)	(0.00404)	(0.00339)
Private	-0.00877**	-0.00885**	-0.00873**	-0.00875**	-0.0102*
	(0.00417)	(0.00410)	(0.00416)	(0.00418)	(0.00523)
State	-0.000587	-0.000644	-0.000442	-0.000492	0.000632
	(0.0111)	(0.0107)	(0.0109)	(0.0109)	(0.0110)
IQ			0.0614	0.0661	0.145*
			(0.118)	(0.111)	(0.0791)
Private R&D	-0.0300	-0.0267	-0.0268	-0.0243	-0.0184
	(0.0551)	(0.0547)	(0.0539)	(0.0546)	(0.0589)
Tertiary	-1.126***	-1.092**	-1.024*	-1.018*	
Education	(0.340)	(0.453)	(0.531)	(0.533)	
Researchers	-0.187	-0.177	-0.171	-0.168	
	(0.138)	(0.145)	(0.148)	(0.148)	
Employment		-0.0609	-0.105	-0.108	-0.881**
S&T		(0.542)	(0.565)	(0.557)	(0.405)
Unemployment		-0.0771	-0.0816	-0.0762	
		(0.168)	(0.176)	(0.188)	
Emp.-density			-0.128	-0.149	
			(0.909)	(0.910)	
GDP p.c.				0.156	0.330
				(0.718)	(0.702)
Constant	4.718**	4.598*	4.893	3.339	-4.005
	(1.672)	(2.337)	(4.153)	(7.487)	(6.994)
Year FE	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES
Observations	240	240	240	240	240
R2-within	0.587	0.587	0.588	0.588	0.571

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix 7: Dep. Var.: Change in patents per GDP in logs

Appendix 8: Dynamic OLS FE: Funds and controls lagged three periods

	(1)	(2)	(3)	(4)	(5)
Patents lag1	-1.104***	-1.111***	-1.113***	-1.113***	-1.095***
	(0.0836)	(0.0837)	(0.0820)	(0.0818)	(0.0775)
EU	-0.00000911	0.000128	0.000300	0.000390	0.000373
	(0.00411)	(0.00413)	(0.00410)	(0.00409)	(0.00438)
Region	0.00367	0.00410	0.00423	0.00439	0.00542
	(0.00575)	(0.00539)	(0.00538)	(0.00546)	(0.00489)
Private	-0.0149**	-0.0161**	-0.0162**	-0.0162**	-0.0181**
	(0.00545)	(0.00564)	(0.00567)	(0.00567)	(0.00655)
State	0.00238	0.00305	0.00325	0.00300	0.00440
	(0.00671)	(0.00656)	(0.00700)	(0.00712)	(0.00579)
IQ			0.0776	0.0856	0.148
			(0.122)	(0.111)	(0.0870)
Private R&D	-0.0457	-0.0348	-0.0319	-0.0276	-0.0220
	(0.0341)	(0.0343)	(0.0316)	(0.0328)	(0.0368)
Tertiary	-1.109***	-0.883**	-0.821	-0.814	
Education	(0.337)	(0.404)	(0.485)	(0.485)	
Researchers	-0.158	-0.131	-0.128	-0.123	
	(0.154)	(0.150)	(0.149)	(0.149)	
Employment		-0.496	-0.542	-0.547	-1.188**
S&T		(0.476)	(0.500)	(0.487)	(0.428)
Unemployment		-0.0681	-0.0704	-0.0606	
		(0.153)	(0.159)	(0.169)	
Emp.-density			0.0550	0.0217	
			(0.942)	(0.910)	
GDP p.c.				0.266	0.406
				(0.762)	(0.752)
Constant	4.518**	3.213	2.805	0.141	-5.097
	(1.856)	(2.135)	(4.229)	(8.267)	(7.519)
Year FE	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES
Observations	240	240	240	240	240
R2-within	0.607	0.609	0.610	0.610	0.601

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix 8: Dep. Var.: Change in patents per GDP in logs

Appendix 9: Researchers as dep. Var. in Dynamic OLS FE: Funds and controls lagged one period

	(1)	(2)	(3)	(4)	(5)
Researchers lag1	-0.333***	-0.346***	-0.345***	-0.382***	-0.382***
	(0.0740)	(0.0704)	(0.0681)	(0.0650)	(0.0671)
EU	0.00138	0.00138	0.00127	0.00111	0.00117
	(0.00126)	(0.00122)	(0.00118)	(0.00111)	(0.00121)
State	-0.00339*	-0.00402**	-0.00442***	-0.00406**	-0.00359*
	(0.00170)	(0.00149)	(0.00154)	(0.00188)	(0.00195)
Region	0.00242**	0.00231*	0.00232*	0.00212	0.00261*
	(0.00111)	(0.00131)	(0.00132)	(0.00146)	(0.00136)
Private	-0.000633	0.000152	0.000143	0.000230	-0.000354
	(0.00176)	(0.00148)	(0.00145)	(0.00141)	(0.00148)
IQ			-0.0591	-0.0763	-0.0532
			(0.0528)	(0.0552)	(0.0513)
Private R&D	0.0754**	0.0694**	0.0681**	0.0635**	0.0713**
	(0.0307)	(0.0289)	(0.0270)	(0.0270)	(0.0266)
Tertiary Education	-0.0683	-0.219	-0.293	-0.309	
	(0.159)	(0.200)	(0.206)	(0.205)	
Employment S&T		0.328	0.371	0.391	0.170
		(0.248)	(0.246)	(0.239)	(0.199)
Unemployment		0.00342	0.00886	-0.00960	
		(0.0743)	(0.0723)	(0.0745)	
Emp.-density			0.134	0.197	
			(0.166)	(0.146)	
GDP p.c.				-0.588*	-0.539*
				(0.321)	(0.300)
Constant	1.167**	2.014**	1.665*	7.628*	6.834**
	(0.547)	(0.706)	(0.922)	(3.962)	(3.164)
Year FE	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES
Observations	240	240	240	240	240
R2-within	0.312	0.324	0.333	0.350	0.334

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix 9: Dep. Var.: Change in researchers per GDP in logs

Appendix 10: Researchers as dep. Var. in Dynamic OLS FE: Funds lagged one, controls lagged two periods

	(1)	(2)	(3)	(4)	(5)
Researchers lag1	-0.278***	-0.283***	-0.286***	-0.314***	-0.308***
	(0.0625)	(0.0580)	(0.0541)	(0.0539)	(0.0545)
EU	0.0000666	0.000195	0.000140	0.000314	0.000502
	(0.00164)	(0.00161)	(0.00170)	(0.00184)	(0.00189)
State	-0.0000630	-0.000812	-0.00100	-0.00108	-0.000892
	(0.00190)	(0.00219)	(0.00214)	(0.00208)	(0.00189)
Region	0.000977	0.00135	0.00145	0.00133	0.00152
	(0.00117)	(0.00126)	(0.00131)	(0.00133)	(0.00120)
Private	-0.00112	-0.000713	-0.000725	-0.000622	-0.000939
	(0.00175)	(0.00184)	(0.00177)	(0.00170)	(0.00180)
IQ			-0.0285	-0.0412	-0.0192
			(0.0370)	(0.0422)	(0.0401)
Private R&D	0.0365	0.0326	0.0325	0.0292	0.0339
	(0.0263)	(0.0262)	(0.0247)	(0.0228)	(0.0237)
Tertiary Education	-0.113	-0.209	-0.243	-0.265	
	(0.114)	(0.144)	(0.153)	(0.164)	
Employment S&T		0.258*	0.288*	0.314*	0.117
		(0.147)	(0.153)	(0.167)	(0.121)
Unemployment		-0.0450	-0.0461	-0.0556	
		(0.0421)	(0.0445)	(0.0438)	
Emp.-density			0.0731	0.123	
			(0.291)	(0.261)	
GDP p.c.				-0.414	-0.328
				(0.337)	(0.372)
Constant	1.344**	2.012***	1.831	6.054	4.635
	(0.483)	(0.645)	(1.153)	(4.231)	(3.720)
Year FE	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES
Observations	220	220	220	220	220
R2-within	0.278	0.289	0.291	0.299	0.283

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix 10: Dep. Var.: Change in researchers per GDP in logs

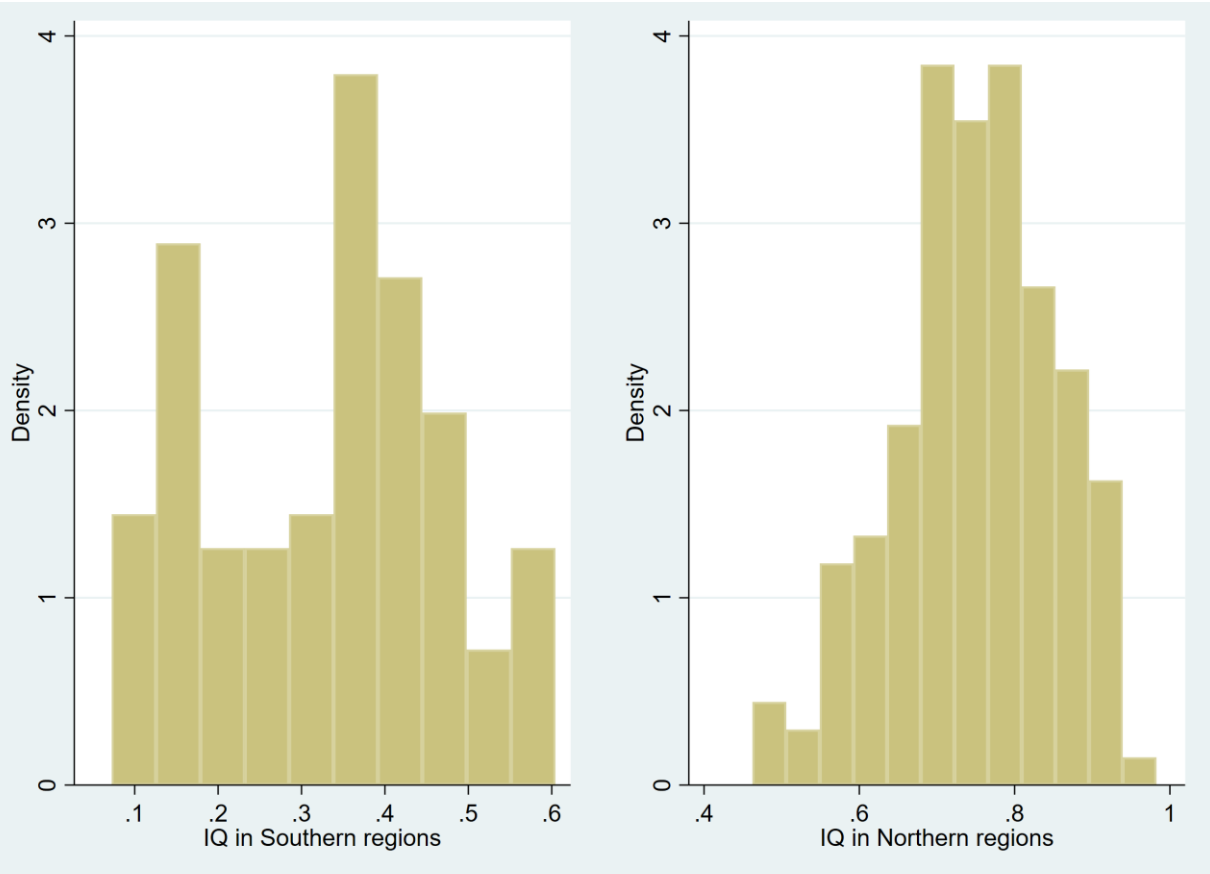
Appendix 11: Researchers as dep. Var. in Dynamic OLS FE: Funds and controls lagged two periods

	(1)	(2)	(3)	(4)	(5)
Researchers lag1	-0.268***	-0.274***	-0.277***	-0.305***	-0.295***
	(0.0701)	(0.0672)	(0.0637)	(0.0578)	(0.0608)
EU	0.00177	0.00185	0.00181	0.00166	0.00170
	(0.00286)	(0.00282)	(0.00276)	(0.00250)	(0.00262)
State	-0.00149	-0.00207	-0.00243*	-0.00228	-0.00165
	(0.00136)	(0.00142)	(0.00140)	(0.00134)	(0.00158)
Region	-0.00119	-0.00110	-0.00102	-0.00109	-0.000787
	(0.00151)	(0.00146)	(0.00154)	(0.00165)	(0.00175)
Private	-0.00103	-0.000361	-0.000310	-0.000246	-0.000955
	(0.00121)	(0.00130)	(0.00124)	(0.00124)	(0.00126)
IQ			-0.0327	-0.0458	-0.0197
			(0.0344)	(0.0394)	(0.0369)
Private R&D	0.0353	0.0309	0.0309	0.0276	0.0333
	(0.0264)	(0.0263)	(0.0241)	(0.0220)	(0.0230)
Tertiary Education	-0.149	-0.249	-0.297*	-0.319*	
	(0.116)	(0.154)	(0.160)	(0.171)	
Employment S&T		0.248	0.287*	0.315	0.0656
		(0.158)	(0.165)	(0.183)	(0.121)
Unemployment		-0.0313	-0.0308	-0.0408	
		(0.0430)	(0.0456)	(0.0444)	
Emp.-density			0.120	0.170	
			(0.309)	(0.280)	
GDP p.c.				-0.416	-0.326
				(0.312)	(0.338)
Constant	1.406***	2.050***	1.722	5.966	4.508
	(0.479)	(0.678)	(1.210)	(4.012)	(3.352)
Year FE	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES
Observations	220	220	220	220	220
R2-within	0.288	0.296	0.299	0.308	0.288

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix 11: Dep. Var.: Change in researchers per GDP in logs

Appendix 12: Institutional Quality in Southern and Northern regions



Appendix 12: Source: Own illustration, based on data from Nifo and Vecchione (2015)

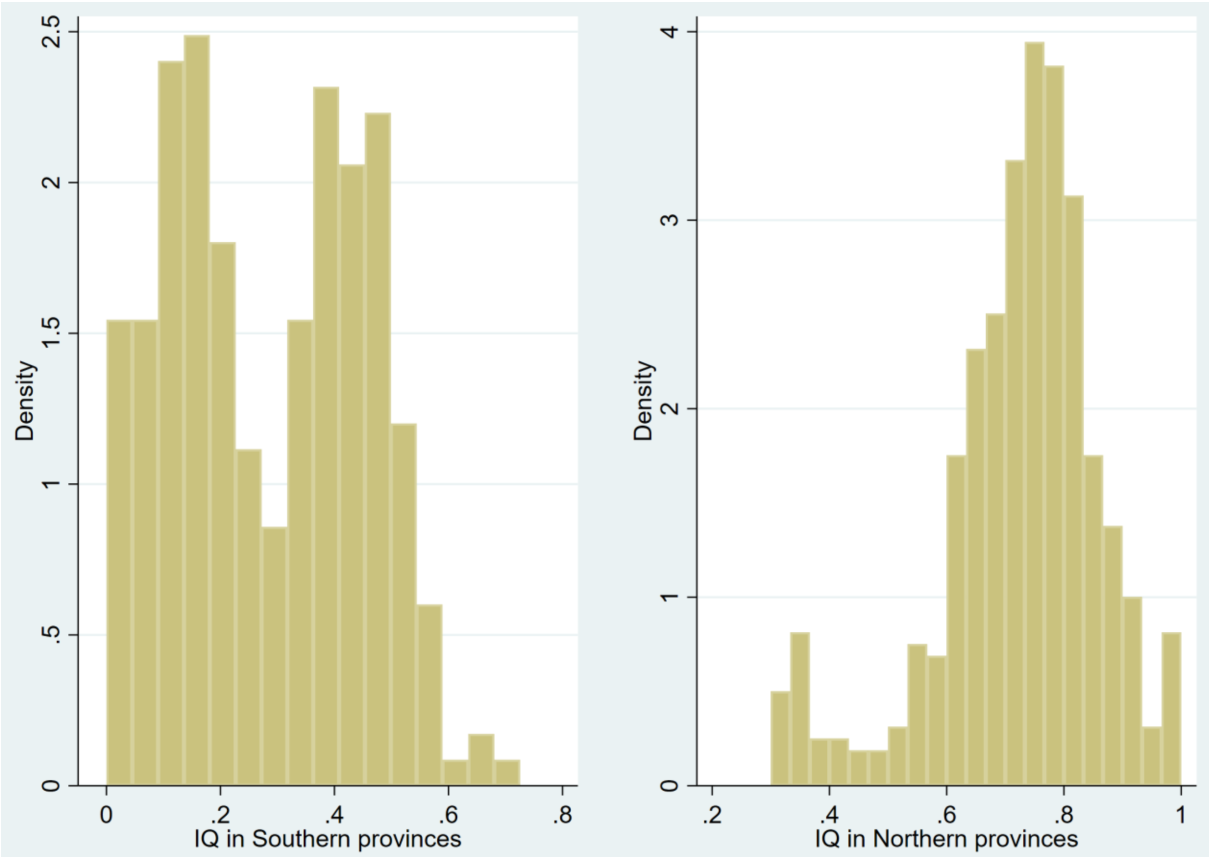
Appendix 13: Static Poisson model excluding spatial spillovers and interaction term

	(1) Funds in t, controls in t-1	(2) Funds in t-1, controls in t-1	(3) Funds in t-1, controls in t-2	(4) Funds in t-2, controls in t-2	(5) Funds in t-2, controls in t-3
EU	0.0100	0.0135	0.00934	-0.00751	-0.00780
	(0.00903)	(0.0105)	(0.00848)	(0.0112)	(0.0129)
State	-0.0181**	-0.0106	-0.0113	0.000865	0.000764
	(0.00916)	(0.00999)	(0.00792)	(0.00960)	(0.0114)
Region	-0.00408	-0.00335	0.000663	-0.00764	-0.00392
	(0.00488)	(0.00547)	(0.00623)	(0.00711)	(0.00785)
Private	0.00339	0.00275	0.000252	0.00554	0.00364
	(0.00386)	(0.00402)	(0.00434)	(0.00415)	(0.00493)
IQ	-0.0374	0.0272	0.237	0.246	0.114
	(0.237)	(0.234)	(0.147)	(0.154)	(0.151)
Tertiary	0.145	0.140	-1.960***	-2.186***	-0.203
Education	(0.543)	(0.528)	(0.704)	(0.749)	(0.974)
Unemp.	0.0514	0.0174	0.162	0.116	-0.0401
	(0.108)	(0.108)	(0.139)	(0.123)	(0.148)
Employment	-0.374*	-0.358*	-0.105	-0.0965	-0.161
Agriculture	(0.213)	(0.215)	(0.226)	(0.207)	(0.292)
Emp.-density	0.296	0.307	0.398*	0.422*	0.00683
	(0.299)	(0.253)	(0.227)	(0.233)	(0.335)
Firmsize	-0.375	-0.457	-0.296	-0.288	-0.863**
	(0.314)	(0.289)	(0.319)	(0.302)	(0.404)
Year FE	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES
Observations	618	618	514	514	404

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix 13: Dependent var.: Patents per GDP

Appendix 14: Institutional Quality in Southern and Northern provinces



Appendix 14: Source: Own illustration, based on data from Nifo and Vecchione (2015)

Appendix 15: System GMM-estimations with endogenous funds in t-1, and controls in t-2

	(1)	(2)	(3)	(4)	(5)
Patents lag1	0.783***	0.621***	0.424**	0.516**	0.448***
	(0.116)	(0.141)	(0.192)	(0.228)	(0.163)
EU	0.0832*	0.0791	0.0410	0.0190	0.00824
	(0.0506)	(0.0620)	(0.0447)	(0.0603)	(0.0475)
State	-0.118**	-0.107*	-0.0973**	-0.101**	-0.0879**
	(0.0510)	(0.0643)	(0.0457)	(0.0465)	(0.0433)
Region	0.0582*	0.0416	-0.00888	-0.0193	-0.0124
	(0.0347)	(0.0339)	(0.0473)	(0.0540)	(0.0448)
Private	0.0101	0.00926	0.0367**	0.0445**	0.0413**
	(0.0205)	(0.0194)	(0.0175)	(0.0225)	(0.0180)
IQ				-0.390	-0.473
				(0.504)	(0.489)
EU spatial lag	0.0271	0.0380	0.0744**	0.0952**	0.0915**
	(0.0360)	(0.0283)	(0.0320)	(0.0458)	(0.0384)
Tertiary Education	4.003*	2.360	-0.607	-1.211	-1.383
	(2.351)	(2.378)	(2.068)	(2.154)	(2.080)
Unemployment		-0.841	-0.103	0.536	0.567
		(0.511)	(0.533)	(0.483)	(0.475)
Employment Agriculture			-1.380**	-2.049***	-2.003***
			(0.607)	(0.625)	(0.631)
Emp.-density			-0.00240	-0.238	-0.334
			(0.643)	(0.573)	(0.547)
Firm size				-1.821*	-1.998**
				(1.027)	(0.951)
GDP p.c.					0.972
					(1.328)
Constant	-10.47*	-4.055	-1.427	3.211	-5.455
	(6.344)	(7.303)	(7.291)	(7.344)	(13.41)
Year FE	YES	YES	YES	YES	YES
Observations	498	494	494	490	490
P-value Hansen-test	0.181	0.216	0.316	0.765	0.692
P-value AR(1)-test	0.000	0.000	0.002	0.001	0.000
P-value AR(2)-test	0.320	0.300	0.434	0.332	0.377

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix 15: System-GMM estimations with dependent var.: Patents in logs

Appendix 16: System GMM-estimations with endogenous funds in t-1, controls in t-2, and interaction term

	(1)	(2)	(3)	(4)	(5)
Patents lag1	0.459*	0.485**	0.506***	0.470**	0.402*
	(0.240)	(0.193)	(0.178)	(0.218)	(0.229)
EU	0.0486	0.0743	0.0727	0.0454	0.0551
	(0.102)	(0.0906)	(0.0624)	(0.0612)	(0.0675)
IQ	4.292***	3.973**	2.264	2.448	1.629
	(1.406)	(1.727)	(2.144)	(1.843)	(1.891)
EU#IQ	-0.240**	-0.225**	-0.208**	-0.151*	-0.163
	(0.101)	(0.108)	(0.0990)	(0.0915)	(0.0992)
State	0.0738	0.0420	0.00793	0.00328	0.0100
	(0.1000)	(0.0973)	(0.0753)	(0.0702)	(0.0764)
Region	-0.00996	-0.0112	-0.0381	-0.0476*	-0.0431*
	(0.0319)	(0.0353)	(0.0329)	(0.0246)	(0.0241)
Private	0.0118	0.00597	0.0270	0.0281*	0.0293*
	(0.0206)	(0.0200)	(0.0195)	(0.0164)	(0.0160)
EU spatial lag	0.0603*	0.0564*	0.0741**	0.0787***	0.0611**
	(0.0346)	(0.0334)	(0.0305)	(0.0269)	(0.0305)
Tertiary Education	-0.159	0.380	-0.900	-1.833	-1.921
	(1.513)	(1.324)	(1.487)	(1.602)	(1.768)
Unemployment		-0.0891	0.251	0.379	0.462
		(0.548)	(0.547)	(0.444)	(0.469)
Employment Agriculture			-1.167**	-1.247**	-1.125*
			(0.545)	(0.538)	(0.632)
Emp.-density			-0.420	-0.292	-0.311
			(0.425)	(0.461)	(0.524)
Firm size				-1.753**	-1.537*
				(0.838)	(0.855)
GDP p.c.					1.970
					(1.549)
Constant	-1.044	-2.160	-3.239	6.424	-13.32
	(4.263)	(4.299)	(4.220)	(6.569)	(14.09)
Year FE	YES	YES	YES	YES	YES
Observations	496	494	494	492	492
P-value Hansen-test	0.108	0.086	0.221	0.371	0.290
P-value AR(1)-test	0.004	0.002	0.000	0.001	0.003
P-value AR(2)-test	0.295	0.306	0.290	0.280	0.368

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix 16: System-GMM estimations with dependent var.: Patents in logs