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ACADEMIC INVENTORS AND THE ANTECEDENTS OF GREEN TECHNOLOGIES. A REGIONAL ANALYSIS OF ITALIAN PATENT DATA

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Academic inventors and the antecedents of green technologies. A regional analysis of Italian patent data

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Abstract

This work investigates the generation of green technologies (GTs) in Italian NUTS 3 regions across time, by focusing on the knowledge generation mechanisms underlying the creation of green patents. Firstly, we hypothesize that inventions in non-green technological domains positively influence the generation of GTs, because the latter occur as the outcome of a recombination process among a wide array of technological domains. Secondly, we hypothesise that the involvement of academic inventors in patenting activity bears positive effects on the generation of GTs, because they are able to manage the recombination across different technological domains. Thirdly, we explore the interaction effect between academic inventors' involvement and non-green technologies to investigate whether the former are especially relevant in presence of higher or lower levels of the latter. We estimate zero-inflated negative binomial, spatial durbin and logistic regressions on a dataset of 103 Italian NUTS 3 regions for which we collected patent and regional data for the time span 1998-2009. The results suggest that both academic inventors and spillovers from polluting technologies bear positive direct effects on the generation of GTs; moreover, we find that academic inventors compensate for low levels of spillovers.

Keywords: green technologies; patents; recombinant knowledge; academic inventors.

Jel codes: O31, Q55, R11

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1 Introduction

A wide body of literature has investigated the determinants of the generation and adoption of green technologies (GTs) (Barbieri et al., 2016). The main motivation behind these studies can be found in the well-known Porter hypothesis, according to which firms introducing GTs in their production processes will obtain the twofold advantage of increasing their productivity and improving their environmental performances (Porter and van der Linde, 1995; Carrión-Flores and Innes, 2010; Carrión-Flores et al., 2013). A major economic issue is represented in this context by the so-called "double externality" problem. Green technological knowledge shares the same features of knowledge as an economic good, leading to market failures and therefore to suboptimal investments in green R&D. In addition, GTs are a source of another externality that is related to the improvement of environment quality (Rennings, 2000).

In this framework, according to the inducement hypothesis, stringent regulatory frameworks drive firms' adoption of GTs. This in turn contributes to the creation of a market for GTs, providing the economic incentive to suppliers for the generation of green inventions (Popp, 2002; Taylor et al., 2005; Popp, 2006; Fischer and Newell, 2008; Popp et al., 2009; Nemet, 2009; Popp, 2010; Acemoglu et al., 2012; Johnstone et al., 2012; Hoppmann et al., 2013). For these reasons, most of the extant literature has focused on the relevance of policy intervention as a determinant of both the generation and adoption of GTs. Somewhat less attention has instead received the investigation of the dynamics underlying the generation of GTs.

In this paper, we intend to fill this gap and shed new lights on the antecedents of green inventions (del Rio González et al., 2009). By opening the black box of GTs, we extend the existing literature in many directions. Firstly, we investigate the extent to which non-green technologies can have an impact on the generation of GTs. Recent contributions indeed stress that the generation of GTs is more likely to occur as the outcome of a recombination process spanning across a wide array of technological domains (Dechezlepetre et al., 2013). More specifically, the combination of green technological domains with non-green ones seems to be a particularly fruitful condition for the generation of new GTs through hybridization (Zeppini et al, 2011).

Secondly, and related to the previous point, we study the role of academic scientists when involved in patenting activity. In fact, it has been shown that scientists are more likely to generate patents that span technological boundaries, suggesting that academic inventors are better able to manage the recombination across different, and not necessarily related, technological domains (Gruber et al., 2013). These arguments lead us to hypothesise that the stock of non-green patents and the involvement of academic scientists positively influence the generation of green patents. Finally, we also explore the interplay between the impact of academic inventors and that of non-green technologies on the generation of GTs, with the aim of investigating the extent to which the former are particularly relevant in presence of higher or lower levels of spillovers from non-green technologies.

We employ a knowledge production function (KPF) approach to test our hypotheses: we estimate the production of green patents as a function of the stock of non-green patents, academic inventors' involvement and a set of control variables at NUTS 3 and 2 level. The latter include industry determinants (i.e. gross value added, industry employment), R&D determinants (i.e. total expenditure in research and development, science and technology graduates, university expenditure in research and development), local knowledge base determinants (i.e. technological variety) and environmental policy determinants (i.e. environmental performance). We run our analysis on a panel dataset of 103 Italian NUTS 3 regions containing patent data covering the period 1998-2009, collected from the OECD Regpat databases and combined with the APE-INV Dataset, along with the Cambridge Econometrics European Regional Database and with data from the Italian Institute for National Statistics and from a national environmental association.

The rest of the paper is organized as follows. In Section 2 we discuss the literature concerned with the generation of green technologies and present our hypotheses. Section 3 presents the data, the variables construction and the methodology. Section 4 shows the results from the econometric analysis. Section 5 provides the conclusions and policy implications of this work.

2 Literature and hypotheses

2.1 Environmental innovation

Environmental innovations are defined by Kemp et al (2010:1) as "new or modified processes, techniques, systems and products to avoid or reduce environmental damage". Because of their characteristics, environmental innovations bring environmental as well as economic benefits to the society, therefore resulting in a win-win situation (Horbach, 2008). In particular, they produce positive spillovers while allowing firms to internalise negative environmental effects. This principle is fully developed by the so-called Porter hypothesis, according to which firms introducing GTs in their production processes will obtain the twofold advantage of increasing their productivity and improving their environmental performances (Porter and van der Linde, 1995; Ambec et al., 2013).

For this reason, a wide body of empirical literature has focused on the drivers of green technologies (Barbieri et al., 2016). In these studies, particular attention has been devoted to the role of environmental technology policy and to the stringency of environmental regulatory frameworks. This interest is rooted in the well-known ‘double externality’ problem, according to which private investments in green technologies are sub-optimal because of the externalities related to the appropriability conditions of technological knowledge and to the social impact of green technologies in terms of improvement to the environment (Rennings, 2000).

Environmental regulation has proven to yield a positive impact on green technologies. The underlying mechanism is based on an inducement effect activated by stringent policy frameworks. Firms are pushed to cope with the increase in production costs due to the incompliance with the regulation trough the introduction of innovations aiming at improving the environmental impacts of production processes, hence meeting the standards set forth by policymakers. These dynamics in turn contribute to the creation of a market for GTs, providing the economic incentive to suppliers (Jaffe and Palmer, 1997; Popp, 2002; Popp, 2006; Fischer and Newell, 2008; Popp et al., 2009; Popp, 2010; Johnstone et al., 2010; Costantini and Mazzanti, 2012; Acemoglu et al., 2012; Hoppmann et al., 2013; Costantini et al., 2015).

According to del Rio González (2009), existing studies have put forth convincing evidence on the determinants of green technologies, focusing on the innovation and diffusion stages. The literature on the antecedents of green inventions is instead substantially underdeveloped at the moment. The notions of recombinant knowledge and collective invention can be far reaching in this respect.

2.2 Recombinant knowledge and the generation of GTs

The recombinant knowledge approach has gained momentum in the early 2000s, and it has profoundly influenced the understanding of the mechanisms underlying the creation of new ideas. Based on an intuition of Joseph Schumpeter, scholars in this domain have long argued that the process of knowledge generation relies heavily on the recombination of existing knowledge components (Schumpeter, 1939; Nelson and Winter, 1982; Henderson and Clark, 1990; Weitzman, 1996). These components include ideas, artifacts and any other fundamental bit of knowledge that may be used to develop innovations (Fleming and Sorenson, 2004).

These intuitions proved to be particularly fertile and paved the way to several theoretical and empirical investigations aimed at assessing the extent to which all components are all alike in the recombination process, or rather some of them are better combinable than others. Technological relatedness has been indicated as a key driver for the success of knowledge recombination. The more the components are related to one another from a technological viewpoint, the higher is the probability of success of recombination dynamics, and the higher is their impact on innovation and economic performances. Different measures of relatedness have been proposed, supporting the validity of these conclusions both at the firm and the regional level (Nesta and Saviotti, 2005; Nesta, 2008; Antonelli et al., 2010; Quatraro, 2010 and 2016; Colombelli et al., 2014).

Recent contributions have applied the recombinant knowledge framework to advance the understanding of the dynamics behind the generation of GTs. Zeppini et al (2011) elaborate a model showing that the combination of green technological domains with non-green ones seems to be extremely fruitful for the generation of new GTs. This is because the recombination allows a paradigm shift from a dominant non-green regime to a clean technology one. Yet, they contend that this is a second-best choice when the costs of environmental policy are accounted for in their model. In a similar vein, Dechezleprêtre et al. (2013) show that GTs are much more cited than non-green technologies, receiving citations from both green and non-green new patents. This suggests that GTs have larger combinatorial potential, in view of their wider scope of application, as compared to other technologies. Also, they find that technologies stemming from the combination between green and non-green technologies outperform 'truly' non-green technologies in terms of impact on the generation of GTs. More recently, Corradini (2017) show that the entry of regions in green technological domains has an inverted U-shaped relationship with the relatedness to the green knowledge accumulated in the area. This result also suggests that green knowledge per se is not sufficient to warrant the development of GTs. Montresor and Quatraro (2018) explore the differential impact of technological relatedness to green and non-green knowledge, showing that both yield positive effects on the local emergence of new green specializations, though the magnitude of the impact of non-green knowledge is larger than that of GTs.

In addition, several examples show that knowledge recombination between green and non-green components has been particularly fruitful for the generation of environmentally relevant innovations: in the integrated photovoltaic and gas-turbine system, wasted heat is collected by photovoltaic devices; in the hybrid car a conventional combustion engine is combined with an electric propulsion system (Jaber et al, 2003); photovoltaic films result from the combination of thin layer technologies and solar cells (Zeppini et al, 2011).

These considerations lead us to spell-out our first hypothesis about the impact of cross-sector spillovers from non-green technological knowledge on the generation of green inventions:

Hp 1: The local availability of non-green knowledge is positively associated to the local generation of green knowledge.

2.3 Academic inventors and green patenting

The recombinant approach proposes that new ideas emerge out of combination of knowledge components dispersed amongst economic agents (Allen, 1983). The generation of new technological knowledge requires therefore the command of a wide array of sources and competences that can hardly be concentrated in one single individual. Invention dynamics are more and more a collective activity, involving the collaboration of different agents able to process knowledge inputs from a variety of sources (Scandura, 2017). The importance of collective dynamics is confirmed by the evidence about the market increase of teamwork organization in knowledge production (Wuchty et al., 2007; Adams et al, 2005; de Solla Price, 1963). Fragmentation and dispersion of knowledge, division of labor and the knowledge burden hypothesis have been proposed as concurrent explanations of this emerging trend (Jones, 2009; Agrawal et al., 2016; Teodoridis, 2017).

The literature on inventors' teams has investigated the determinants of successful teamwork knowledge production. In this framework, the educational background of inventors has been found to be one of the most important drivers, particularly whether it is in science or engineering (Allen, 1977). According to these studies, academic inventors, because of their distinct educational endowment, possess different knowledge sets and skills that allow them to successfully recombine knowledge bits across different technological domains. In fact, prior research shows that inventors with higher educational attainment possess a better understanding of technological problem solving, they are less constrained by their cognitive abilities and more receptive toward innovation, and therefore more likely to engage in boundary-spanning activities (March and Simon, 1958; Hambrick and Mason, 1984; Gagné and Glaser, 1987; Walsh, 1995; Pelled, 1996; Hargadon, 2006). Similarly, Gruber et al. (2013) stress that scientists are more likely to generate patents than span technological boundaries as compared to engineers, suggesting that inventors endowed with a strong scientific background are able to manage the recombination across different, and not necessarily related, technological domains.

Furthermore, recent contributions show that universities have a prominent role in the generation of environmental innovation, because the knowledge required for its implementation is more complex and more ‘codified’ than that required for other types of innovation (Cainelli et al., 2012; Cainelli et al., 2015). Analysing data from the Italian Community Innovation Survey, De Marchi and Grandinetti (2013) show that GTs are more sensitive to collaborations with universities and research centres, with respect to standard innovations. At the European level, Triguero et al. (2013) find that small and medium firms interacting with institutional agents, including research institutes, agencies and universities, perform better in terms of green patents. Similarly, a recent study by Fabrizi et al. (2018) investigating the role of regulatory policies and research networks for environmental innovation across European countries, confirms that the contribution of universities and public research centres in green research network is positive and higher than the contribution of private firms. These studies point to the argument that GTs need a large set of competencies and skills and, therefore, collaboration with ‘high profile’ agents that possess those competencies and skills are fundamental to the successful generation of environmental innovation.

Based on this conceptual background, we hypothesize that the involvement of inventors from universities in patenting activity bears positive effects on the generation of GTs, by increasing the production of green patents. Provided the level of cumulated human capital necessary to access academic jobs, it can be assumed that academic inventors have a higher level of education than those employed in industry. Since higher levels of education are associated with higher abilities and willingness to recombine knowledge across technological domains, this being a fundamental pre-condition for the creation of environmentally sound inventions, we hypothesise that the intensity of involvement of academic scientists is positively associated with the amount of green patents generated. Therefore, we formulate our second hypothesis as follows:

Hp 2: The higher is the involvement of academic inventors in local patenting dynamics, the higher is the local generation of green knowledge.

2.4 Interaction between non-green knowledge and academic inventors

The previous hypothesis points to the positive impact of academic inventors on the generation of green knowledge because of their ability to move beyond the constraints of cognitive proximity. However, academic inventors also play an important role in mitigating the impact of geographical proximity on the effects of knowledge spillovers. There is extensive literature in the field of geography of innovation stressing that knowledge spillovers are localized because of the interplay of institutional factors and because of the higher absorptive capacity of co-localized agents that is due to complementarities and similarities in their competence set (Saxenian, 1994; Audretsch and Feldman, 1996; Feldman, 1999; Antonelli, 2001; Ellison et al., 2010). We can reasonably expect that the effects of the spillovers from non-green knowledge identified in the first hypothesis are also geographically bound. Low levels of local non-green knowledge likely hinder the generation of GTs. All other things being equal, it is very unlikely that knowledge spillovers can flow from other distant regions because of the constraining role of space.

However, some literature has proposed that not all knowledge flows are all alike, and that the binding role of geography hinders the flow of different kinds of knowledge to different extents. Particularly, the exchange of knowledge among scientists within epistemic communities has been found to be less sensitive to spatial decay. A proposed explanation to these specific patterns is related to the nature of knowledge exchanged in epistemic communities, with respect to the distinction between tacit and codified knowledge (Breschi and Lissoni, 2001; Quatraro and Usai, 2017). In this framework, the ICT revolution is considered responsible of the decrease in the marginal costs of transmitting codified knowledge across geographic space, which have become invariant with respect to geographical distance (Steinmuller, 2000; Cowan et al., 2000).

Academic inventors can have a further role in this respect, by mitigating the dependence of the generation of GTs on the local spillovers from non-green technologies, because of their involvement in global epistemic communities and in the exchange of codified knowledge across dispersed places. In other words, according to Hp1, we expect that low levels of spillovers from local non-green knowledge are associated with low levels of GTs generation. However, in view of the arguments above, in places where there is high intensity of academic inventors one would expect the bounded effects of knowledge spillovers to be weaker, because of their capacity to access geographically dispersed knowledge sources. In other words, academic inventors can be considered as agents favouring the substitution of cross-regional knowledge spillovers for local knowledge spillovers. This compensation effect translates into an expected negative sign of the interaction between academic inventors' involvement and local knowledge spillovers variables. We can spell our last hypothesis as follows:

Hp 3: The higher is the involvement of academic inventors in local patenting dynamics, the lower is the impact of local spillovers from non-green technologies on the local generation of green knowledge.

In the rest of the paper we will present and discuss our empirical analysis and its results. In the next section we describe the data and the methodology that we have used in the econometric analysis and we motivate the choice of the implemented estimators.

3 Data, variables and methodology

3.1 Data sources

We test our hypotheses on a panel dataset of 103 Italian NUTS 3 regions (provinces) with data available from 1998 to 2009. The dataset includes 1,236 records. It is made up of inventor and patent data from the database on "Academic Patenting in Europe" (APE-INV)[3], combined with patent information form the OECD Regpat database and from the OECD Indicator of Environmental Technologies. Regional administrative data at NUTS 2 and 3 level have been collected from the Cambridge Econometrics European Regional Database. Additional data have been collected from the Italian Institute for National Statistics (ISTAT) and from an Italian environmental association.

3.2 Dependent variables

The dependent variable is constructed from the OECD Indicator of Environmental Technologies (OECD, 2011) combined with the OECD Regpat database (Maraut et al, 2008). The first one is a classification of green technologies based on the International Patent Classification (IPC), presenting the following seven environmental areas: (a) general environmental management, (b) energy generation from renewable and non-fossil sources, (c)

[3] APE-INV is a project on academic patenting in Europe that has been funded by the European Science Foundation. See Lissoni (2013) and project website for full details http://www.esf-ape-inv.eu/.

combustion technologies with mitigation potential, (d) technologies specific to climate change mitigation, (e) technologies with potential or indirect contribution to emission mitigation, (f) emission abatement and fuel efficiency in transportation, and (g) energy efficiency in buildings and lighting. The second is a database of technological classes linked to regions according to the addresses of the applicants and inventors. In the Italian case, it provides information on NUTS 2 (i.e. "Regioni", or regions) and 3 ("Province" or provinces) levels.

In this paper, we use a dependent variable that measures the province-level stock of green patents, following the perpetual inventory method as in Peri (2005). We initiate the stock in year 1977, which is the first year when we observe Italian patents in the OECD Regpat database, and use the recursive formula $K\_GT_{i,t} = (1-d)K\_GT_{i,t-1} + N\_GT_{i,t}$, where $N\_GT_{i,t}$ is the flow of province level patent applications previously defined and d is the obsolescence rate applied to depreciate the stock of past patent applications $K\_GT_{i,t-1}$. The value chosen for d is 15%, commonly used in the literature (Keller, 2002).[4] The variable hence created allows to take into account not only the net amount of green patents generated, but also the cumulated green knowledge generated by past patenting activity.[5]

Descriptive statistics are reported in Table 2. The stock of green patents has mean equal to 6.8 and standard deviation of 20.07, thus showing right skewness. In fact, 75% of the observations have a stock that is smaller than 5. In addition, 15% of observations have zero stock of GTs. To get a closer look at variation across province and across time, we plot the province time-trend of $K\_GT_{i,t}$ split into four geographical macro-areas (see Figure 1).[6] Besides the presence of outliers in the North West (i.e. Milan and Turin), in the North East (i.e. Vicenza, Bologna and Modena) and in the Center (i.e. Roma, Pisa and Firenze), two considerations clearly emerge from the graphs. Firstly, we notice a clear positive trend only in few provinces located in the North and, to some extent, in the Center, whereas in the South there is a mix of increasing and decreasing stock of green patents across time. Secondly, while the well-known

[4] This methodology has some drawbacks, such as the approximation of a linear depreciation scheme with a geometric one, the use of the same rate across regions, hence ruling out territorial differences, and some necessary degree of measurement error. However, given the availability of the data, it provides a good approximation for the purposes of our work.

[5] We also compute a dummy variable called GT_DUMMY, equal to 1 when there is generation of GTs, zero otherwise. We use this as dependent variable in a robustness check where we estimate the probability of generation of GTs (see section 4.2).

[6] North West provinces are those of Piedmont, Valle d'Aosta, Liguria and Lombardy; North East provinces belong to Veneto, Friuli-Venezia Giulia, Emilia-Romagna, and Autonomous provinces of Trento and Bolzano (formerly Trentino-Alto Adige); Central provinces are in Tuscany, Marche, Umbria and Lazio; Southern provinces belong to Abruzzo, Molise, Puglia, Campania, Basilicata, Calabria, Sicilia and Sardegna.

Italian North-South gap in economic development is also mirrored by patent data, what is striking is that this gap seems to be widening across time, particularly in the post-2000 period.

3.3 Independent variables

The first factor we look at is cross sector spillovers from non-green technologies. We are interested in the role played by the cumulated knowledge in non-green domains for the generation of green technologies. Therefore, we use the stock of non-green patents applications, $K\_NOGT_{i,t}$, calculated in the same way as the stock of green patent applications, by using the recursive formula $K\_NOGT_{i,t} = (1-d)K\_NOGT_{i,t-1} + N\_NOGT_{i,t}$, where $N\_NOGT_{i,t}$ is the count of non-green patents applications. In addition, we use the squared term of the stock of non-green patents $K\_NOGT\_SQ_{i,t}$ to investigate whether spillovers have a quadratic relationship with our dependent variable. Similarly to the stock of green patents, the stock of non-green is right-skewed, presenting a mean value of 197.9 and a standard deviation is 563.7 (see Table 2).

The second factor we consider is the involvement of academic inventors in patenting activities. The APE-INV database allows the identification of academic inventors and their home address within the list of patent applications at the European Patent Office.[7] From this, it is possible to identify provinces where there are academic inventors and tag patent applications with at least one academic inventor among the list of inventors. Based on this information, we work out two variables that will be used to measure academic inventors' involvement. Firstly, we create a dummy having value 1 for provinces presenting patenting activity that involves academic inventors, and 0 otherwise. The dummy $ACAD\_PAT_{i,t}$ has a mean value of 0.47, indicating that 47% of provinces across time presents academic patenting activity (see Table 2). Secondly, we compute the share of patents involving academic inventors by dividing the count of patents involving at least one academic inventor per the total count of patents produced in a given province at a given time. The distribution of the variable $SHARE\_ACAD_{i,t}$ shows that 52% of the province-year observations has no involvement at all; the mean value is 0.027, indicating that on average, 2.7% of patents involve academic inventors, with a standard deviation of 0.06. In the empirical analysis, we employ the share hence calculated as well as its squared term ($SHARE\_ACAD\_SQ_{i,t}$) to control for curvilinear effects.

[7] The identification of academic inventors is available for the time span 1996-2009. In this paper we shorten it to years 1998-2009, for which we have complete information on all other variables.

Finally, to test our third hypothesis of an interaction effect between academic inventors' involvement and cross-sector spillovers from polluting technologies, we generate two interaction terms: $ACAD\_PAT_{i,t} * K\_NOGT_{i,t}$ and $SHARE\_ACAD_{i,t} * K\_NOGT_{i,t}$, where the spillover variable is multiplied for the dummy indicating academics' involvement and for the share of patents involving academics.

3.4 Control variables

We create a number of control variables to account for various province-level characteristics. In the first place, we control for industry related factors, given sectoral differences in propensity to patent. Hence, we use industry gross value added ($IND\_GVA_{i,t}$) and employment in industry ($IND\_EMP_{i,t}$). We use the Cambridge Econometrics' European Regional Database (ERD) to construct them. This is a highly disaggregated dataset across regional and sub-regional dimensions, based on Eurostat REGIO database and the AMECO dataset of the European Commission's Directorate General Economic and Financial Affairs.

Secondly, we control for R&D and human capital factors to capture the determinants of GTs related to the local R&D structure and availability of skilled workforce. We employ total R&D expenditure ($R\&D\_EXP_{i,t}$), R&D expenditure of universities ($R\&D\_UNI_{i,t}$), and science and technology graduates ($S\&T\_GRAD_{i,t}$). We collect data from ISTAT databases, which provide information on them at NUTS 2 level. To compute the NUTS 3 corresponding variables, we weight the NUTS 2 variables for the NUTS 3 share of regional GDP.

We also control for the heterogeneity of technological domains at province level so to account for the structure of the local technological base. We create a variable ($TECH\_VAR_{i,t}$) that measures technological variety, calculated from the probability of co-occurrence of patent technological classes within province patent applications.[8] The higher the variable, the higher

[8] Following Quatraro (2010), we measure technological variety in province knowledge bases using the information entropy index (Attaran and Zwick, 1987). For the purpose of this work, the entropy index measures the degree of disorder or randomness of the province knowledge base starting from the probability of co-occurrence of patent technological classes within province patent applications. Each technological class j is linked to class m when the same patent is assigned to both of them. The higher the number of patents jointly assigned to classes j and m, the stronger this link is. Since technological classes are listed in patent documents, we refer to the link between j and m as the co-occurrence of both of them within the same patent document. Given p_{jm} the probability of co-occurrence of the two technological classes, a two dimensional entropy measure (E) is expressed as follows: $E = \sum_{j=1}^{q} \sum_{m=1}^{w} p_{jm} \log_2(1/p_{mj})$. In other words, E measures the variety of co-occurrences of technological classes j and m in a given province. A multidimensional index, which accounts for all patent technological classes in the province, measures the heterogeneity of all classes. The higher the index, the higher is technological variety in a given province.

is technological variety in a given province. The data source for its creation is the OECD Regpat dataset on technological classes linked to provinces.

Finally, we control for environmental policies through an index of environmental performance created by Legambiente, an Italian non-profit organisation dedicated to environmental issues. The Legambiente index ($ENV\_PERF_{i,t}$) provides a score for each of the 103 province capital cities, based on several indicators of e.g. air quality, green areas, drinking water quality, energy consumption, waste recycling performance. Legambiente releases a ranking of Italian cities on the basis of the city scores. This ranking implicitly provides an assessment of the performance of local policy-makers in managing environmental protection tasks (Bianchini and Revelli, 2013).[9]

All control variables and their descriptive statistics are reported in Table 1 and Table 2. Table 3 presents the correlation table of all variables. The dependent variable is highly correlated with the variable measuring spillovers from non-green domains; it is also positively and significantly correlated with the dummy indicating academic inventors' involvement and with most of the control variables.

TABLES 1, 2, 3 ABOUT HERE

FIGURE 1 ABOUT HERE

3.5 Methodology

The literature dealing with the empirical analysis of regional innovation performance is often based on the implementation of the so-called knowledge production (KPF). The KPF is among the pillars of the applied economics of innovation (Griliches, 1979, 1990, 1992; Romer, 1990; Link and Siegel, 2007) and it has been widely applied in several contexts including firms, regions, industries and countries. In line with extant research, we employ an extended KPF where the stock of green patents ($K\_GT_{i,t}$) is the dependent variable and cross-sector spillovers ($K\_NOGT_{i,t}$), academic inventors' involvement ($ACAD\_PAT_{i,t}$, $SHARE\_ACAD_{i,t}$) and their interaction are among the regressors. Among the right-hand side variables of our models we

[9] Clearly, urban environmental quality is not entirely under control of city governments. Regional and central government also play a role, and there may be relevant spillovers from nearby jurisdictions. However, given their institutional role in environmental monitoring, regulation and protection, the impact of city-level governments on environmental performance can be substantial (Lo Prete and Revelli, 2017).

also include a vector of control variables ($X_{i,t}$), NUTS 2 fixed effects (ρ_i) and year fixed effects (τ_t). Therefore, we estimate the following equations:

(1a) $K\_GT_{i,t} = \beta_0 + \beta_1\ K\ NOGT_{i,t} + \beta_2\ ACAD\ PAT_{i,t}\ + \gamma X_{i,t} + \sum\rho_i + \sum\tau_t + \varepsilon$

(1b) $K\_GT_{i,t} = \beta_0 + \beta_1\ \ K\ NOGT_{i,t} + \beta_2\ ACAD\ PAT_{i,t} + \beta_3 ACAD\ PAT_{i,t}\ * K\ NOGT_{i,t} + \gamma X_{i,t} + \sum\rho_i + \sum\tau_t + \varepsilon_{i,t}$

(2a) $K\_GT_{i,t} = \beta_0 + \beta_1\ K\ NOGT_{i,t} + \beta_2\ SHARE\ ACAD_{i,t}\ + \gamma X_{i,t} + \sum\rho_i + \sum\tau_t + \varepsilon$

(2b) $K\_GT_{i,t} = \beta_0 + \beta_1\ K\ NOGT_{i,t} + \beta_2\ SHARE\ ACAD_{i,t}\ + \beta_3 SHARE\ ACAD_{i,t}\ * K\ NOGT_{i,t} + \gamma X_{i,t} + \sum\rho_i + \sum\tau_t + \varepsilon$

The analysis of the antecedents of the generation of GTs poses an additional problem that is due to a number of year-province observations for which we observe zero green patents. These are around 15% of the sample. In this framework, investigation is needed to establish whether the observed zeros are due to the overall absence of patenting activity or to a specific lack of green patents nonetheless featuring some degree of technological activities. The zero-inflated negative binomial (ZINB) model represents the most appropriate solution at hand because it allows the zeros in the dependent variable to be generated by a different process with respect to the positive values. The ZINB model runs simultaneously two equations: a binary logistic equation to model the zeros (inflation part of the model) and a negative binomial equation to model the dependent variable. The logit equation allows to distinguish between provinces where there is patenting activity, but not green patents, and regions where there is no patenting activity at all. We base our inflation model on the stock of total patent (both green and non-green) in each province ($K\_TOT_{i,t}$).

In order to exploit the panel data structure, we employ year and region fixed effects. We employ NUTS 2 fixed effects to allow convergence of the ZINB model and we cluster standard errors at NUTS 3 level so to account for province-specific effects. In addition, we employ 1 and 2 year lagged regressors to further rule out reverse causality concerns. In particular, while the vector of control variables is lagged by one year only, the stock of non-green patents and the academic inventors' variables are lagged by two years. Using larger time lags for the factors that should have major influence on the generation of GTs is reasonable in light of the time it usually takes to generate an invention, apply for patent and, eventually, having it granted. In fact, besides inventive activity, the application and granting process can take up to, on average, 18-24 months. Finally, given the skewness of some of the continuous variables, we transform them to linearize their trend. We apply the inverse hyperbolic sine transformation, which allows not to lose any zero in the variables.[10] For consistency and to ease interpretation of the results, we transform all continuous variables using the same method.

4 Results

4.1 Main results

The main results are reported in Tables 4 and 5. In table 4 we present the ZINB regressions of models (1a) and (1b), where the dummy variable ACAD_PAT measures academic inventors' involvement. In columns 1-3 we produce the results on the subsamples of observations for which we observe no missing data on any of the variables. This corresponds to 927 observations over years 2001-2009. In columns 4-6 we replicate the regressions on the full sample of 1,236 observations after excluding the variable ENV_PERF, for which data are only available from 2001 onwards.

The variable measuring the stock of patents in non-green domains (K_NOGT) is consistently positive and significant (at 1-5% level) in all models. This confirms the first hypothesis of our work, according to which the production of GTs substantially depends upon the stock of non-green technologies. This leads us to assert that there are substantial spillovers from dirty to clean technologies. Similarly, the variable ACAD_PAT is positive and significant (at 1% level) in all models, thus confirming our second hypothesis of a positive contribution of academic inventors to the generation of GTs. Thanks to their peculiar endowment in skills, academic scientists are able to fruitfully recombine knowledge bits from various technological domains, which is a pre-condition for the successful generation of green technologies. Finally, the coefficients of the interaction term between K_NOGT and ACAD_PAT displayed in columns 3 and 6 are negative and significant (at 1% level), hence providing support to the third hypothesis of this work. Therefore, we find a compensation effect of academic inventors'

[10] This is an alternative to the Box-Cox transformations, defined by the following formula: $inverse\ y = \log[y_i + (y_i^2 + 1)^{1/2}]$. Except for very small values of y, the inverse sine can be interpreted as a standard logarithmic variable. However, unlike a logarithmic variable, the inverse hyperbolic sine is defined at zero (Johnson, 1949; Burbidge et al, 1988; MacKinnon et al, 1990).

involvement on cross-sector spillovers, due to the fact that academic inventors favour the substitution of cross-regional knowledge spillovers for local knowledge spillovers.

The coefficients of K_NOGT in the full models in columns 3 and 6 indicate that the expected stock of green patents increases by 0.04 units for each unit increase in the stock of non-green patents. Therefore, K_GT increases by a factor of 1.04.[11] The coefficients of ACAD_PAT in columns 3 and 6 suggest that the expected stock of GTs for provinces where academic inventors are involved in patenting activity is 1.1[12] times the expected stock of GTs for provinces with no academic inventors' involvement, holding all other variables constant. Therefore, K_GT is 10% higher in provinces where academic inventors' are involved in patenting.

The negative coefficients of the interaction terms indicate that the strong involvement of academic members in inventors' teams compensate for the lack of appropriate levels of local knowledge spillovers, most likely because of the ability of academic inventors to engage in spatially unbounded knowledge exchanges. Specifically, in areas characterised by high intensity of academic inventors, the decrease of K_NOGT has no negative effects on the expected value of K_GT. On the contrary, we find that thanks to the compensation effect, a unit decrease in K_NOGT increases the expected value of K_GT by a factor of 0.02.[13] in provinces where academic inventors are involved in patenting activity. Figures 2 and 3 support our findings and further show that for lower levels of K_NOGT, provinces where academic inventors are involved in patenting activity display higher predicted levels of GTs, whereas the opposite holds for high levels of K_NOGT.

As for the other regressors, it is worth noticing that the squared term of the spillover variable is negative and significant (at 1-5% level) in all models where it is included, hence suggesting an inverted U-shaped relationship between the stock of non-green technologies and the stock of GTs. In other words, while patents in non-green domains positively influence the generation of green patents, this is not true for high levels of the former. Industry determinants also matters for the generation of GTs, particularly the variable IND_GVA, whose coefficients are positive and significant (at 5-10% level) in the full sample estimations. R&D variables' coefficients are positive and significant (at 1-5% level) in almost every estimation, especially

[11] This is the incidence rate ratio, obtained by exponentiating the coefficient.
[12] This is exp(0.10).
[13] This is 1-exp(-0.02).

in the case of total R&D expenditure and R&D expenses of universities, thus confirming the relevance of the R&D regional infrastructure for the generation of GTs. Technological variety is positively and significantly related (at 5-10% level) to the dependent variable in the estimates on the full sample, suggesting that the higher heterogeneity of technological domains is, the higher the stock of GTs.

It is also worth noting that our proxy for environmental policies never displays significant effects. This is not surprising, given the idiosyncratic features of the empirical context. In fact, even though Italy is part of the European environmental policy framework, it must be stressed that strong cross-country differences in the way policies are implemented still persist within Europe. In particular, Italy features very low levels in various OECD indicators, notably displaying low control of corruption and low levels of transparency and stability of environmental policy, as compared to the other OECD countries (Damania et al., 2003; Haščič et al., 2009; Johnstone et al., 2010).[14]

The bottom part of Table 4 presents the estimation of the inflate part of the model: the inflate variable (K_TOT) predicting excessive zeros is negative and significant (at 1-10% level), which indicates that the higher the past stock of total patents, the lower the probability that there is no patenting activity in a given province. In other words, the more patents in K_TOT, the more likely that provinces display patenting activity (albeit green or not).

In Table 5, we present the results of models (2a) and (2b) where the involvement of academics into patenting activity is measured with the variable SHARE_ACAD. As in Table 4, the first three regressions are run on the subsample of observations for which there are no missing data point for every single variable (2001-2009), whereas the last three regressions are carried out on the full sample (1998-2009). The results are very similar to those in Table 4 with the only exception that the share of patents involving academic inventors is not statistically significant in columns 3 and 6, where the interaction term is included. The coefficients of SHARE_ACAD in models 2 and 5 indicate an increase in K_GT by a factor of 10 and 4 respectively, due to a unit increase in the share of patents involving academics. We also find that SHARE_ACAD displays a quadratic behaviour with respect to the dependent variable, as shown by the negative and significant coefficient (at 5-10% level) of SHARE_ACAD_SQ in

[14] According to Marin and Mazzanti (2013: p. 378): "manufacturing [...] has also not adapted to the new climate change policy scenario, and even the environmental Italian policy as a whole has somewhat lagged behind other leading countries in terms of policy efforts".

all models where it is included. Similarly to the spillover variable, SHARE_ACAD has an inverted U-shaped relationship with K_GT, thus implying that the proportion of patents involving academic inventors positively influence the generation of GTs up to a certain level, after which the relationship turns to be negative. This is consistent with the existing evidence on the dynamics of pecuniary knowledge externalities in areas characterized by congestion of technological activities (Antonelli et al., 2011). The interaction terms in columns 3 and 6 support indicate a compensation effect between academic inventors and spillovers from polluting technologies, as their coefficients are negative and significant (at 5% level). Finally, control variables in Table 5 have very similar coefficients and significance of those in Table 4.

All in all, our results confirm the hypotheses of this work. Firstly, there is a spillover effect from non-green domains to green domains, although this is true up to a given point only. Secondly, provinces displaying involvement of academic inventors into patenting activities have higher levels of green patents stock. When accounting for the exact share of patents involving academics, we find a fairly large effect but that is true up to a certain level. Finally, our data support the argument of compensation effects between academic inventors and local spillovers, whereby the higher is academics' involvement in local patenting dynamics, the lower are the adverse effects of insufficient local spillovers on the generation of GTs.

4.2 Robustness checks

In this section, we show the results of various robustness checks. In the first place, we replicate our analyses on two subsamples of observations created on the basis of geographical macro-areas, by splitting the sample into Northern and Central-Southern Italy. We do so in light of the above illustrated remarkable differences in the stock of GTs across Italian provinces (Figure 1). We suspect that Northern provinces display different trends with respect to the rest of the provinces. Tables 6 and 7 show the results for the Northern and Center-South samples, respectively: in both tables, columns 1 and 2 present the results of models (1a) and (1b), while the estimates of models (2a) and (2b) are displayed in columns 3 and 4. We show only the main regressors of interest, but all control variables and year fixed effects are include in every model. Furthermore, we employ area fixed effects at the level of macro-regions, as follows: North-Eastern and North-Western regions (Table 6), Centre and South regions (Table 7). A geographical pattern emerges from these results since the spillover effect is found in Northern provinces only; the role of academic inventors is confirmed in both areas but it is slightly stronger in Southern provinces; the interaction effect between academic inventors and cross-sector spillovers is negative and significant in Northern provinces only.

The results in Tables 6 and 7 show a geographical divide, hence suggesting that the geographical dimension matters. For this reason, our second robustness check consists of a spatial regression model to further investigate such issues. We are interested in the effect of cross-sector spillovers and academic inventors when their spatial effects are accounted for. To do so, we implement a spatial Durbin auto-regressive model where we control for both spatially lagged regressors of interest.[15] Various estimations show that there is no spatial effect of academic inventors.[16] Therefore, we present only the estimates where the spatial lag of the stock of non-green patents is included. The results are presented in Table 8, where we show the Main, Direct, Indirect and Total Effects. We present the coefficients of the main independent variables only, but all control variables are included in the estimates. The spatial model so implemented includes year and NUTS 2 fixed effects. The results confirm Hp 1 (see column 1 and 4, 5 and 8), and Hp 2 before introducing the interaction effect (see columns 1 and 4), while Hp 3 is only qualitatively confirmed. Furthermore, the results show that spillovers from non-green patents also have spatial effects, as can be noted from the statistically significant coefficient of K_NOGT is columns 3 and 7 and from the statistically significant spatial lag of K_GT in columns 1 and 5. Therefore, we find that the local generation of GTs positively benefits from intra and extra region cross-sector spillovers.

The third and last set of regressions that we present to corroborate our results are shown in Tables 9 and 10. We implement a Logit model to estimate whether and to what extent the probability of generating green patents is influenced by the independent variables. We employ NUTS 2 and year fixed effect to account for the panel data structure. The dependent variable is a dummy indicating whether there is any green patenting activity in a given province at a given time ($GT\_DUMMY_{i,t}$). This is created assigning value 1 every time the flows of green patents ($N\_GT_{i,t}$) has positive values, 0 when it has value zero. The results are presented in Table 9, while the marginal effects are reported in Table 10. The coefficients confirm Hp 1 and 2 of this work, while Hp 3 is only qualitatively confirmed. Therefore, the probability of generation of GTs is positively influenced by cross-sector spillovers and by the involvement of academic inventors in patenting activities. Specifically, the probability of GTs generation increases by 2

[15] We use the Stata command XSMLE (Stata 13).
[16] Not reported here.

percentage point due to an increase in the stock of non-green patents. It increases by 5 percentage point in provinces where academic inventors are involved in patenting activity and by 32 percentage point due to an increase in the share of academic patents involving academic inventors.

5 Conclusion

This work has investigated the knowledge generation mechanisms underlying the creation of green technologies. We focus on the role of non-green technological domains, academic inventors, and the combination of their effects for the generation of GTs. To investigate these issues, we build a panel dataset of 103 Italian provinces observed through years 1998-2009, combining patent data from the OECD Indicator of Environmental Technologies and the OECD Regpat databases, inventor data from the APE-INV dataset, and regional administrative data from the Cambridge Econometrics ERD and ISTAT. The main empirical analysis consists of zero-inflated negative binomial regressions, while robustness checks include spatial panel data regressions and logistic regressions.

Our results suggest positive cross-sector spillovers from non-green technological domains, hence supporting the first hypothesis of our work. Specifically, the previous stock of non-green patents positively influence the stock of green ones. In addition, our data show that Italian provinces featuring involvement of academic inventors in patenting activity display higher stock of green patents generated, thus supporting hypothesis 2. We find that both the dummy variable indicating whether there is any involvement of academic inventors and the exact share of province-level patents involving academics, are positively and significantly affecting the generation of GTs. Hypothesis 3 is also confirmed by our data in the main results, which show that academic inventors facilitate the substitution of cross-regional knowledge spillovers for local knowledge spillovers. The robustness checks carried out confirm the main findings, although the compensation effect between academics and spillovers is not always statistically confirmed. Additionally, our data show that spillovers from polluting technologies are more relevant in Northern Italian regions than in Southern areas, while the role of academic inventors is stronger in Southern regions than in the rest of the country. The interaction effect is found in Northern provinces only. We also find that cross-sector spillovers from neighbouring regions are fairly relevant for the local generation of green patents. Finally, the probability of generation of GTs is positively influenced by both cross-sector spillovers and academic inventors.

This work has few caveats, including the well-known limits of patent statistics as indicators of technological activities and the approximation of academia-business interaction with the involvement of academic inventors in patenting activity. Yet, previous studies highlighted the usefulness and reliability of patents to measure the production of new knowledge, notably in the context of regional innovation performances (see e.g. Acs et al., 2002). Prior research also shows the key role of academic inventors for companies' innovation and for regional innovation (see e.g. Meyer, 2004; Murray, 2004; Lissoni, 2010).

Nonetheless, this work contributes to the academic debate in many ways. First of all, we shed lights on the knowledge recombination process behind green innovation. In particular, our results are in line with extant research as far as the recombination of different and distant technological domains are concerned. Specifically, in line with the theoretical model developed by Zeppini et al. (2011) and with the empirical results of Corradini (2017) and Montresor and Quatraro (2018), we show that knowledge recombination between green and non-green components is fruitful for the generation of environmentally relevant innovations through hybridization. Secondly, as vastly supported by the literature on patent inventors, we show that inventors are key actors in the knowledge recombination activity (see e.g. Gruber et al, 2013). Precisely, academic inventors, because of their educational endowment, are better able to recombine knowledge components across different technological domains (see e.g. Hargadon, 2006). Additionally to previous studies, we show that there are compensation effects between cross-sector spillovers and academic inventors, whereby academic inventors reduce the dependence of the generation of GTs on the local spillovers from polluting technologies. This finding further reinforces the key role of academic inventors in the green innovation process.

We believe this work contributes to opening the black box of green innovation because it uncovers the knowledge dynamics behind its generation. Furthermore, by exploring the role of academic inventors for the generation of GTs, this work combines two streams of the economics of innovation literature that have only rarely intersected, namely university-industry interactions and environmental innovation. Our analysis also has important policy implications grounded on the need to boost the generation of GTs, so to achieve a "smart growth" as defined by the Europe 2020 strategy.[17] In particular, our analysis contributes the debate on the

[17] http://ec.europa.eu/europe2020/europe-2020-in-a-nutshell/index_en.htm

importance of optimal policy mixes for the promotion of technology-driven sustainability transition, which points to the need of coordination of environmental and science and technology policies (Crespi and Quatraro, 2015; Crespi et al. 2015; Costantini et al., 2015). First, our analysis indicates that for technology policies aiming at supporting the creation at GTs to be effective, resources should not be fully allocated exclusively to green R&D, due to the relevance of knowledge inputs from non-green technological activities. Moreover, much of the extant literature has stressed the importance of accessing external resources and participating to innovation networks for the generation of GTs. Our results suggest that science and technology policies should support the generation of GTs by explicitly stimulating university-industry interactions, particularly the involvement of academic scientists in teams of inventors. This would indeed ensure heterogeneity of competencies and availability of the necessary skills to combine knowledge inputs from diverse knowledge sources, even when they are geographically dispersed.

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7 Tables

		VARIABLES	Description	Data source	Time span
Dependent variables	1	K_GT	Province-level stock of green patents	OECD Regpat, OECD Indicator of Environmental Technologies	1998-2009
	2	GT_DUMMY	Dummy equal to 1 for generation of GTs, 0 for no generation	OECD Regpat, OECD Indicator of Environmental Technologies	1998-2009
Independent variables	3	K_NOGT	Province-level stock of non-green patents	OECD Regpat, OECD Indicator of Environmental Technologies	1998-2009
	4	SHARE_ACAD	Share of patents involving academic inventors	Academic Patenting in Europe Database (APE-INV)	1998-2009
	5	ACAD_PAT	Dummy equal to 1 for SHARE_ACAD>0, 0 for SHARE_ACAD=0	Academic Patenting in Europe Database (APE-INV)	1998-2009
Control variables	6	IND_GVA	Industry gross value added	Cambridge Econometrics' European Regional Database	1998-2009
	7	IND_EMP	Employment in industry	Cambridge Econometrics' European Regional Database	1998-2009
	8	R&D_EXP	Total R&D expenditure	Italian Institute for National Statistics	1998-2009
	9	R&D_UNIV	University R&D expenditure	Italian Institute for National Statistics	1998-2009
	10	S&T_GRAD	Science and Technology graduates	Italian Institute for National Statistics	1998-2009
	11	TECH_VAR	Technological variety, heterogeneity of technological domains	OECD Regpat	1998-2009
	12	ENV_PERF	Environmental performance score at city level	Legambiente	2001-2009
Fixed effects	13	YEAR	Dummies	-	-
	14	NUTS 2	Dummies	-	-

Table 1 Variable list.

		VARIABLES	N	mean	sd	min	max
Dependent vars	1	K_GT	1,236	6.798	20.07	0	204.5
	2	GT_DUMMY	1,236	0.373	0.484	0	1
Independent vars	3	K_NOGT	1,236	27.72	563.7	-170.2	5,717
	4	SHARE_ACAD	1,133	0.0269	0.0590	0	1
	5	ACAD_PAT	1,133	0.476	0.500	0	1
Control vars	6	IND_GVA	1,236	2,531	3,498	140.3	30,424
	7	IND_EMP	1,236	49.89	61.02	3.185	497.0
	8	R&D_EXP	1,236	147,649	275,369	3,685	2.418e+06
	9	R&D_UNIV	1,236	46,547	61,852	1,086	595,992
	10	S&T_GRAD	1,228	1.544	1.721	0.0693	16.50
	11	TECH_VAR	1,236	4.441	2.220	0	9.430
	12	ENV_PERF	927	0.502	0.0884	0.213	0.746
Fixed effects	13	YEAR	12	-	-	-	-
	14	NUTS 2	20	-	-	-	-

Table 2 Descriptive statistics.

		1	2	3	4	5	6	7	8	9	10	11	12
1	K_GT	1											
2	GT_DUMMY	0.36*	1										
3	K_NOGT	0.91*	0.33*	1									
4	SHARE_ACAD	0	-0.02	-0.02	1								
5	ACAD_PAT	0.25*	0.33*	0.24*	0.48*	1							
6	IND_GVA	0.85*	0.44*	0.92*	-0.01	0.33*	1						
7	IND_EMP	0.83*	0.46*	0.88*	-0.01	0.36*	0.99*	1					
8	R&D_EXP	0.79*	0.34*	0.73*	0.05	0.3*	0.74*	0.71*	1				
9	R&D_UNIV	0.63*	0.31*	0.59*	0.16*	0.35*	0.62*	0.62*	0.92*	1			
10	S&T_GRAD	0.51*	0.32*	0.44*	0.15*	0.34*	0.43*	0.43*	0.68*	0.73*	1		
11	TECH_VAR	0.43*	0.51*	0.44*	0.06	0.49*	0.59*	0.62*	0.43*	0.37*	0.39*	1	
12	ENV_PERF	0.03	0.19*	0.06	-0.03	0.19*	0.12*	0.12*	0.02	0.13*	-0.05	0.4*	1

Table 3 Pairwise correlation. Significance level 0.05 or more.

VARIABLES	1 K_GT	2 K_GT	3 K_GT	4 K_GT	5 K_GT	6 K_GT
K_NOGT	0.0309**	0.0327***	0.0477***	0.0250**	0.0270**	0.0435***
	(0.0124)	(0.0124)	(0.0126)	(0.0119)	(0.0118)	(0.0123)
K_NOGT_SQ		-0.0329**	-0.0276**		-0.0342***	-0.0282**
		(0.0133)	(0.0131)		(0.0115)	(0.0115)
ACAD_PAT	0.154***	0.128***	0.107***	0.143***	0.123***	0.0971***
	(0.0502)	(0.0445)	(0.0389)	(0.0473)	(0.0425)	(0.0367)
ACAD_PAT*K_NOGT			-0.0189***			-0.0215***
			(0.00695)			(0.00654)
IND_GVA	0.589	0.488	0.510	0.714**	0.604*	0.613*
	(0.382)	(0.370)	(0.368)	(0.339)	(0.331)	(0.327)
IND_EMP	-0.440	-0.336	-0.373	-0.501	-0.393	-0.425
	(0.387)	(0.383)	(0.380)	(0.362)	(0.362)	(0.357)
R&D_EXP	0.200	0.273**	0.279**	0.186	0.263**	0.275**
	(0.123)	(0.123)	(0.123)	(0.118)	(0.120)	(0.120)
S&T_GRAD	0.264*	0.301**	0.302**	0.0169	0.0329	0.0303
	(0.147)	(0.148)	(0.150)	(0.0876)	(0.0886)	(0.0906)
R&D_UNIV	0.0385***	0.0334***	0.0305***	0.0390**	0.0343**	0.0321**
	(0.0114)	(0.0114)	(0.0118)	(0.0153)	(0.0146)	(0.0149)
TECH_VAR	0.239*	0.181	0.164	0.259**	0.203*	0.186*
	(0.128)	(0.125)	(0.123)	(0.116)	(0.111)	(0.109)
ENV_PERF	-0.0226	-0.205	-0.184			
	(0.505)	(0.480)	(0.480)			
Constant	-7.138***	-7.068***	-7.086***	-7.289***	-7.184***	-7.194***
	(1.593)	(1.583)	(1.575)	(1.448)	(1.425)	(1.410)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
NUTS 2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Inflate						
K_TOT	-1.566***	-1.664***	-1.795***	-3.347	-2.787*	-2.753*
	(0.477)	(0.472)	(0.471)	(2.534)	(1.647)	(1.421)
Constant	-30.72***	-14.81***	-14.52***	-11.21	-11.12**	-12.35***
	(1.585)	(1.552)	(1.528)	(11.37)	(4.887)	(4.196)
lnalpha	-47.26***	-32.67***	-394.9***	-23.30***	-17.30***	-43.25***
	(0.0840)	(0.101)	(0.105)	(0.0841)	(0.0311)	(0.0765)
Observations	927	927	927	1,236	1,236	1,236
AIC	2283.1	2278.9	2278.7	2945.5	2938.3	2936.6
BIC	2476.4	2477.0	2481.7	3160.6	3158.5	3161.9
Log Likelihood	-1101.6	-1098.4	-1097.4	-1430.8	-1426.2	-1424.3
McFadden's R2	0.254	0.256	0.257	0.262	0.265	0.266

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4 ZINB regressions. Time span 2001-2009 (col 1-3) and 1998-2009 (col 4-6). Measure of academic inventors' involvement : ACAD_PAT.

VARIABLES	1 K_GT	2 K_GT	3 K_GT	4 K_GT	5 K_GT	6 K_GT
K_NOGT	0.0327***	0.0364***	0.0459***	0.0268**	0.0297**	0.0377***
	(0.0125)	(0.0124)	(0.0132)	(0.0119)	(0.0118)	(0.0123)
K_NOGT_SQ		-0.0340**	-0.0331**		-0.0359***	-0.0356***
		(0.0137)	(0.0136)		(0.0118)	(0.0117)
SHARE_ACAD	0.804*	2.366***	1.438	0.906***	1.323**	0.00899
	(0.413)	(0.906)	(1.061)	(0.300)	(0.571)	(0.746)
SHARE_ACAD_SQ		-5.629**	-8.786*		-0.828	-1.620*
		(2.783)	(4.811)		(0.760)	(0.921)
SHARE_ACAD*K_NOGT			-0.370**			-0.335**
			(0.146)			(0.135)
IND_GVA	0.580	0.511	0.505	0.695**	0.585*	0.578*
	(0.384)	(0.372)	(0.370)	(0.340)	(0.332)	(0.330)
IND_EMP	-0.424	-0.328	-0.371	-0.478	-0.364	-0.408
	(0.388)	(0.383)	(0.380)	(0.365)	(0.366)	(0.359)
R&D_EXP	0.214*	0.242*	0.293**	0.203*	0.266**	0.323***
	(0.124)	(0.130)	(0.125)	(0.118)	(0.124)	(0.121)
S&T_GRAD	0.244*	0.267*	0.241	0.0250	0.0275	0.0205
	(0.146)	(0.148)	(0.152)	(0.0865)	(0.0895)	(0.0914)
R&D_UNIV	0.0385***	0.0324***	0.0303***	0.0351**	0.0318**	0.0297**
	(0.0111)	(0.0114)	(0.0116)	(0.0142)	(0.0142)	(0.0142)
TECH_VAR	0.256*	0.174	0.164	0.271**	0.203*	0.198*
	(0.131)	(0.125)	(0.123)	(0.119)	(0.111)	(0.110)
ENV_PERF	-0.0402	-0.270	-0.196			
	(0.510)	(0.480)	(0.478)			
Constant	-7.259***	-6.756***	-7.011***	-7.380***	-7.132***	-7.467***
	(1.610)	(1.602)	(1.571)	(1.465)	(1.454)	(1.423)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
NUTS 2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Inflate						
K_TOT	-1.563***	-1.668***	-1.659***	-2.967	-2.629**	-2.568**
	(0.468)	(0.471)	(0.461)	(2.188)	(1.221)	(1.093)
Constant	-14.26***	-14.40***	-14.49***	-10.49	-12.72***	-12.90***
	(1.557)	(1.544)	(1.512)	(6.535)	(3.502)	(3.097)
lnalpha	-18.06***	-111.3***	-58.26***	-17.83***	-24.61***	-22.15***
	(0.0906)	(0.0876)	(0.0955)	(0.0834)	(0.0792)	(0.0727)
Observations	927	927	927	1,236	1,236	1,236
AIC	2286.3	2280.0	2278.6	2947.1	2940.1	2938.4
BIC	2479.5	2482.9	2486.3	3162.1	3165.4	3168.8
Log Likelihood	-1103.1	-1098.0	-1096.3	-1431.6	-1426.0	-1424.2
McFadden's R2	0.253	0.257	0.258	0.262	0.265	0.266

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5 ZINB regressions. Time span 2001-2009 (col 1-3) and 1998-2009 (col 4-6). Measure of academic inventors' involvement : SHARE_ACAD.

VARIABLES	1 K_GT	2 K_GT	3 K_GT	4 K_GT
K_NOGT	0.0322**	0.0499***	0.0345**	0.0415***
	(0.0140)	(0.0162)	(0.0142)	(0.0147)
K_NOGT_SQ	-0.0430***	-0.0364***	-0.0454***	-0.0444***
	(0.0119)	(0.0113)	(0.0120)	(0.0117)
ACAD_PAT	0.0709	0.0953*		
	(0.0530)	(0.0562)		
ACAD_PAT*K_NOGT		-0.0271**		
		(0.0113)		
SHARE_ACAD			1.643*	0.0286
			(0.841)	(1.076)
SHARE_ACAD*K_NOGT				-0.434***
				(0.166)
Constant	-4.203**	-4.335**	-4.010**	-4.477**
	(1.871)	(1.825)	(1.905)	(1.856)
Control variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Area FE	Yes	Yes	Yes	Yes
Inflate				
Linvkcap	-7.420	-7.476	-7.475	-7.492
	(5.169)	(5.658)	(5.497)	(5.623)
Costant	20.24*	20.35	20.40	20.41
	(12.14)	(13.35)	(13.04)	(13.29)
lnalpha	-41.44***	-42.02***	-52.56***	-17.72***
	(0.0785)	(0.0715)	(0.0871)	(0.0563)
Observations	552	552	552	552

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6 ZINB regressions. Subsample of Northern provinces. Time span 1998-2009. Measure of academic inventors' involvement : ACAD_PAT (col 1-2) and SHARE_ACAD (col 3-4).

VARIABLES	1 K_GT	2 K_GT	3 K_GT	4 K_GT
K_NOGT	0.0149	-0.0243	0.0176	0.0162
	(0.0151)	(0.0351)	(0.0151)	(0.0190)
K_NOGT_SQ	-0.0535**	-0.0604**	-0.0570**	-0.0575**
	(0.0263)	(0.0288)	(0.0268)	(0.0273)
ACAD_PAT	0.178**	0.386**		
	(0.0841)	(0.174)		
ACAD_PAT*K_NOGT		0.0410		
		(0.0302)		
SHARE_ACAD			0.917**	1.072
			(0.368)	(1.196)
SHARE_ACAD*K_NOGT				0.0285
				(0.200)
Constant	-5.357***	-5.569***	-5.432***	-5.427***
	(1.661)	(1.698)	(1.699)	(1.694)
Control variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Area FE	Yes	Yes	Yes	Yes
Inflate				
K_TOT	-2.940***	-2.947***	-2.870***	-2.864***
	(0.667)	(0.671)	(0.631)	(0.635)
Constant	-11.57***	-11.41***	-11.86***	-11.45***
	(2.908)	(2.981)	(2.406)	(2.420)
lnalpha	-21.41***	-21.37***	-21.25***	-21.38***
	(0.170)	(0.168)	(0.198)	(0.211)
Observations	684	684	684	684

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7 ZINB regressions. Subsample of Centre-South provinces. Time span 1998-2009. Measure of academic inventors' involvement : ACAD_PAT (col 1-2) and SHARE_ACAD (col 3-4).

VARIABLES	1 Main	2 LR_Direct	3 LR_Indirect	4 LR_Total	5 Main	6 LR_Direct	7 LR_Indirect	8 LR_Total
K_NOGT	0.116***	0.116***	0.209*	0.325**	0.121***	0.120***	0.210*	0.330***
	(0.0156)	(0.0157)	(0.125)	(0.128)	(0.0174)	(0.0176)	(0.115)	(0.118)
K_NOGT_SQ	0.00394	0.00442	-0.399	-0.395	0.00525	0.00595	-0.404	-0.399
	(0.0289)	(0.0274)	(0.380)	(0.387)	(0.0292)	(0.0273)	(0.342)	(0.347)
ACAD_PAT	0.123**	0.121**	0.000505	0.122*	0.105	0.103	-0.00251	0.100
	(0.0568)	(0.0559)	(0.0362)	(0.0641)	(0.0664)	(0.0653)	(0.0265)	(0.0662)
ACAD_PAT*K_NOGT					-0.00557	-0.00607	-0.000207	-0.00627
					(0.0117)	(0.0114)	(0.00301)	(0.0120)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NUTS 2 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial lag K_NOGT	0.208*				0.212**			
	(0.107)				(0.107)			
Spatial lag K_NOGT_SQ	-0.379				-0.381			
	(0.309)				(0.308)			
rho	-0.0462				-0.0517			
	(0.223)				(0.224)			
sigma2_e	0.355***				0.354***			
	(0.0494)				(0.0494)			
Observations	1,236				1,236			
R-squared	0.749				0.749			
Number of NUTS 3	103				103			

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8 Spatial Durbin model. Sample 1998-2009. Measure of academic inventors' involvement: ACAD_PAT.

VARIABLES	1 GT_DUMMY	2 GT_DUMMY	3 GT_DUMMY	4 GT_DUMMY
K_NOGT	0.150***	0.161***	0.154***	0.164***
	(0.0351)	(0.0435)	(0.0351)	(0.0340)
K_NOGT_SQ	-0.0167	-0.0141	-0.0212	-0.0220
	(0.0442)	(0.0459)	(0.0442)	(0.0442)
ACAD_PAT	0.324*	0.271		
	(0.170)	(0.227)		
ACAD_PAT*K_NOGT		-0.0150		
		(0.0417)		
SHARE_ACAD			2.222**	-0.754
			(1.037)	(4.059)
SHARE_ACAD*K_NOGT				-0.539
				(0.721)
Control variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
NUTS 2 FE	Yes	Yes	Yes	Yes
Constant	-14.82***	-14.82***	-15.27***	-15.50***
	(4.035)	(4.031)	(3.970)	(4.031)
Observations	1,200	1,200	1,200	1,200
Pseudo R-sq	0.315	0.316	0.316	0.316

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9 Logit regressions. Sample 1998-2009. Dependent variable: GT_DUMMY. Measure of academic inventors' involvement: ACAD_PAT (col 1-2) and SHARE_ACAD (col 3-4).

VARIABLES	1 GT_DUMMY Marginal effects	2 GT_DUMMY Marginal effects	3 GT_DUMMY Marginal effects	4 GT_DUMMY Marginal effects
K_NOGT	0.0221***	0.0225***	0.0226***	0.0211***
	(0.00502)	(0.00500)	(0.00501)	(0.00578)
K_NOGT_SQ	-0.00246	-0.00207	-0.00311	-0.00323
	(0.00649)	(0.00674)	(0.00648)	(0.00648)
ACAD_PAT	0.0477*	0.0488*		
	(0.0250)	(0.0262)		
ACAD_PAT*K_NOGT		-		
SHARE_ACAD			0.327**	0.170
			(0.152)	(0.250)
SHARE_ACAD*K_NOGT				-
Observations	1,200	1,200	1,200	1,200

Table 10 Average marginal effects of Logit regressions in Table 9.

8 Figures

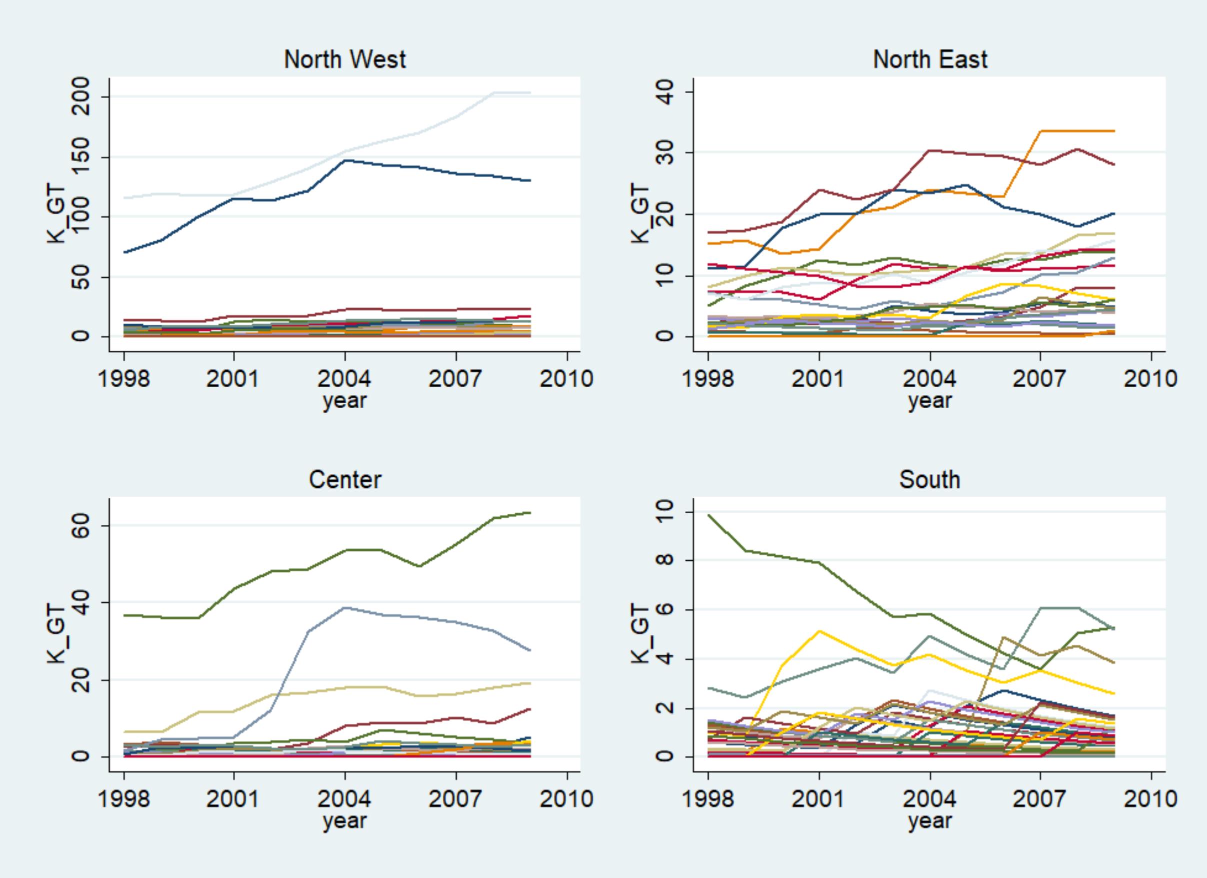

Figure 1 Distribution of the stock of GTs across geographical area.

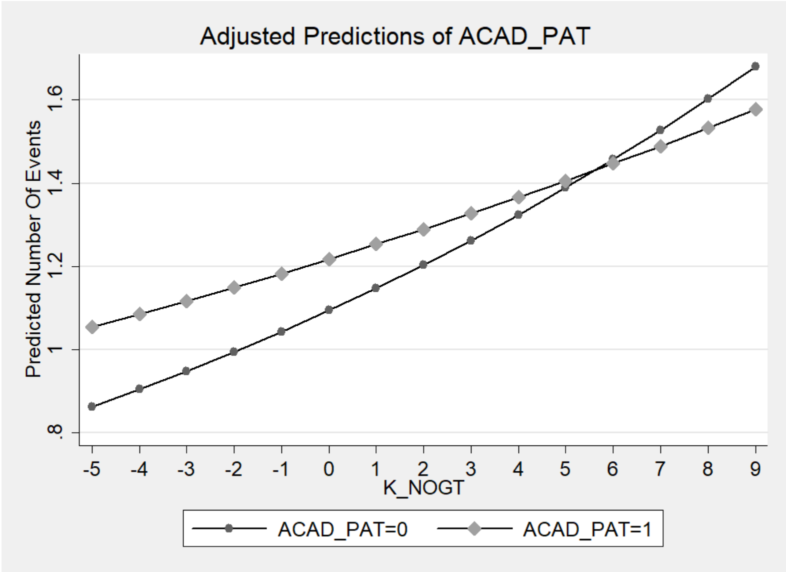

Figure 2 Interaction term Table 4 column 3.

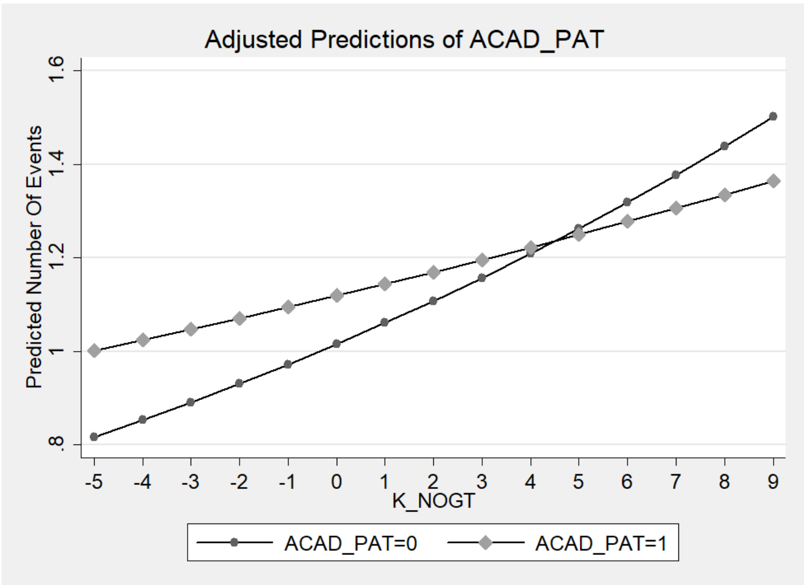

Figure 3 Interaction term Table 4 column 6.