ISSN 2279-9362

Collegio Carlo Alberto

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Gianluca Orsatti
Francesco Quatraro
Alessandra Scandura

No. 617
December 2020

Carlo Alberto Notebooks

www.carloalberto.org/research/working-papers

Regional differences in the generation of green technologies: the role of local recombinant capabilities and academic inventors

Gianluca Orsatti[a,b] Francesco Quatraro[a,b] Alessandra Scandura[a,b]

a) Department of Economics and Statistics Cognetti de Martiis, University of Torino
b) BRICK, Collegio Carlo Alberto

ABSTRACT. This paper investigates the association between region-level recombinant capabilities and the generation of green technologies (GTs), together with their interplay with the intensity of academic involvement in innovation dynamics. The analysis focuses on Italian NUTS 3 regions, over the period 1998-2009. We show that the local capacity to introduce novel combinations is positively and strongly associated to the generation of GTs, while the involvement of academic inventors in local innovation dynamics shows an interesting compensatory role when local contexts lack such capacity.

Jel Classification Codes: O33; R11

Keywords: green technologies, academic inventors, recombinant novelty

1 Introduction

The decoupling of economic growth from environmental degradation has become a major policy concern. In December 2019, the European Commission presented the European Green Deal, a document articulating guidelines and actions to make the EU's economy environmentally sustainable in the long run, and to achieve climate neutrality by 2050.

The academic debate has long focused on these issues, stressing that innovation plays a major role in helping firms to improve their environmental performances. The term eco-innovation encompasses any kind of change, both technological and non-technological, serving the objective to reduce the environmental risk associated to economic actions (Kemp and Pearson, 2007; Barbieri et al., 2016). According to an established tenet in the literature, environmental regulation is key to boost investments in eco-innovations enabling compliance and allowing for the joint improvement of economic and environmental performances (Porter and van der Linde, 1995; Rennings, 2000).

While former investigations of the determinants and effects of eco-innovations have focused on their adoption and generation at the firm-level, more recently a new wave of studies have enquired into the geography of eco-innovation, by stressing the existence of important regional differences in the generation of eco-innovations, and in particular of green technologies (GTs). Extant literature has investigated the sources of these differences, as well as of differential patterns of technological specialization in green technologies (Horbach et al., 2012; Ghisetti and Quatraro, 2013 and 2017; Quatraro and Scandura, 2019; Montresor and Quatraro, 2019; Tanner, 2014; Perruchas et al., 2020; Santoalha and Boschma, 2020).

Most of these studies have looked, on the one hand, at the role of environmental regulation in influencing cross-regional differences in the generation of eco-innovations. Other studies, on the other hand, framed the discussion in the evolutionary economic geography approach, to investigate the extent to which relatedness is a driver of regional technological specialization in the green domain, and which factors may act as enablers or facilitators that mitigate the effect of cumulativeness and path-dependence. However, scant attention has been devoted to the antecedents of GTs, i.e. to the very dynamics behind their generation, and to how these affect differential regional patterns (del Río Gonzalez, 2009; Quatraro and Scandura, 2019).

This paper aims at filling this gap, by investigating how the regional capacity to deal with technological novelty, together with the involvement of academic inventors, is associated with the generation of GTs. To do so, we elaborate on the notion of recombinant capabilities (Carnabuci and

Operti, 2013) to extend it to the regional domain and introduce the concept of *regional recombinant capabilities*. We develop a theoretical framework combining this approach with the recent literature on the inherent complexity of GTs, to spell out the main hypothesis that the capacity of regional agents to manage infrequent and unprecedented combination of knowledge inputs is associated with better performances in the production of GTs (Orsatti, 2019; Orsatti et al., 2020a and 2020b; Barbieri et al., 2020). Our second hypothesis concerns the impact of the involvement of academic inventors in view of their documented capacity to conduct research spanning technological boundaries, and the possible substitution effect in areas characterized by a low degree of recombinant novelty (Quatraro and Scandura, 2019).

The empirical analysis implements a knowledge production function (KPF) framework at the Italian provincial level. Precisely, it focuses on a balanced panel of 103 Italian NUTS 3 regions observed over the period 1998–2009. Our results support the hypothesis according to which regional recombinant novelty is positively associated with better performances in terms of GT generation. Moreover, consistent with previous empirical evidence, we also confirm the positive correlation between the local presence of academic inventors and the generation of GTs. Most importantly, the involvement of academic inventors in patenting activities seems to mitigate underperformances in GTs associated with scarce local capacity to engage in recombinant novelty.

The rest of the paper is organized as follows. Section 2 elaborates the theoretical framework and spells out the working hypotheses. In Section 3 we describe the data sources, the variables and the empirical approach. Section 4 provides the results of the empirical analysis, while Section 5 offers a discussion of the findings and the main conclusions.

2 Theoretical Background

2.1 Environmental innovation, the recombinant approach and the complexity of GTs

There are many definitions of environmental innovation (EI). The seminal one proposed by Kemp and Pearson (2007) refers to any kind of innovation, both technological and non-technological, involving products, processes, services, management and business practices resulting in a reduction of environmental risk, pollution and other negative impacts of resources use (including energy use) compared to relevant alternatives (Kemp and Pearson, 2007: p. 7). Following the well-known Porter hypothesis, the study of the determinants of EIs[1] has received much

[1] See Barbieri et al. (2016) for a recent comprehensive survey of the literature on the determinants and effects of environmental innovation.

attention, because of the expected twofold impact in terms of both economic and environmental performances (Porter and van der Linde, 1995; Ambec et al., 2013). This literature has been influenced by the debate on the specific characteristics of EIs, vis-à-vis generic innovations, and in particular by the so-called 'double externality' problem, and the related regulatory push-pull effect (Rennings, 2000). Consequently, empirical efforts have mainly focused on testing the effect of environmental regulation on the generation and adoption of EIs. Because of the empirical problems concerning the operationalization of EIs, most of the extant literature has restricted the scope of the analysis to the determinants of green technologies (GTs), which are a subset of EIs that can reliably be measured with patent data (Barbieri et al., 2016).

While the research on the drivers of EIs in general, and on GTs in particular, has been quite fertile in the recent years, little is known about their antecedents, i.e. the dynamics leading to the generation of new technologies in this domain (del Río Gonzalez, 2009). Former studies have stressed the relevance of the recombinant knowledge approach in this direction (Zeppini et al., 2011; Quatraro and Scandura, 2019; Orsatti et al., 2020a; Barbieri et al., 2020).

The recombinant approach is rooted in the Schumpeter's view of innovation as the outcome of an unceasing process of recombination of different knowledge components. The literature aiming at understanding both the mechanisms behind combinatorial activities and the way in which different combinatorial modes affect the outcome of the inventive activity flourished over time (Weitzman, 1996 and 1998; Fleming 2001; Fleming and Sorenson, 2001). In this direction, the relatedness degree among technological components has been found to be a key factor affecting the success of recombination efforts (Nesta and Saviotti, 2005; Nesta, 2008; Antonelli et al., 2010; Quatraro, 2010 and 2016; Colombelli et al., 2014).

The analyses focusing on recombinant dynamics leading to the generation of GTs have identified a number of peculiar aspects that differentiates EIs from non-environmental innovation. For instance, Zeppini et al. (2011) articulate a model in which the generation of GTs stems from a combinatorial process conducted across different and loosely related areas of the knowledge landscape. This is because combination amongst 'distant' technologies is more likely to engender a paradigmatic shift from a dominant non-green regime to a clean technology one (Nightingale, 1998; Fleming, 2001). Patent-level analyses have provided empirical evidence of the higher complexity of GTs, as compared to non-green technologies; in addition, the combinations they impinge upon are on average novel ones, i.e. combinations of technological components that had never been tried before (Messeni Petruzzelli et al., 2011; Barbieri et al., 2020).

For these reasons, collective invention dynamics have been found to be especially important in this domain. The access to external knowledge components loosely related to one another is better managed when the inventive process is carried out by teams involving researchers with heterogeneous backgrounds or endowed with skills allowing for the exploration of wide areas of the knowledge space (Quatraro and Scandura, 2019). Similarly, inventor teams' recombinant capabilities[2] have proved to be relevant in this context. In particular, the experience and capacity of team members to manage novel combinations, i.e. recombinant creation capabilities, is crucial for the successful generation of GTs (Orsatti et al. 2020a). The extension of the recombinant capabilities framework to the regional domain can provide a fertile ground to frame the relationship between novelty and the generation of GTs from an economic geography viewpoint.

2.2 Regional innovation capabilities, recombinant novelty and GTs

An increasing number of studies have investigated the patterns of GTs production at the geographical level. Part of the literature focuses on the determinants and effects of these technology while emphasising the role of the regulatory framework (see e.g. Ghisetti and Quatraro, 2013 and 2017). More recently, new evidence has been produced to explain the evolutionary patterns of regional diversification in the GT domain. The main findings concern the impact of knowledge relatedness, suggesting that technological spillovers from areas outside the green domain are an important driver for the entry of regions in green technological specializations (Corradini, 2017; Montresor and Quatraro, 2019; Quatraro and Scandura, 2019; Santoalha and Boschma, 2020).

These studies, framed in the evolutionary economic geography approach, are based on the extension of the Penrosian resource-based theory to the regional domain. Accordingly, regions are the locus of the historical process of accumulation of competences stemming from the execution of economic or technological activities. For this reason, the diversification of regional portfolios of economic and technological activities are more likely to happen in areas that are coherent with the existing local specializations (Neffke et al., 2018).

Similar to firms' dynamic capabilities, *regional innovation capabilities* refer to the ability of local agents and institutions to command and coordinate systemic interactions for the production of new knowledge (Foss, 1996; Lawson and Lorenz, 1999; Romijn and Albu, 2002). Such capabilities "emerge over time as an outcome of the increase of innovation activities within the system and the

[2] The concept of recombinant capabilities, proposed by Carnabuci and Operti (2013), is defined as the ability of a firm's members to manage the combinatorial process to produce innovations. They distinguish between recombinant creation and recombinant reuse. The former concerns the introduction of novel and unexplored combinations, while the latter is related to the refinement and improvement of existing combinations.

working of learning dynamics which enhance agents' capacity to interact and combine external with internal inputs" (Quatraro, 2009: p. 1336).

The appreciation of the recombinant dynamics behind the generation of innovations calls for the refinement of this framework to introduce the concept of *regional recombinant capabilities*. These refer to the capacity of local innovation ecosystems to activate combinatorial processes aiming at the introduction of novelties. Understanding the generation of new technologies at the regional level entails therefore understanding the extent to which localized learning dynamics and systemic interactions can activate new and unprecedented combinations rather refinement and improvement of already known combinations.

As recalled in Section 2.1, GTs are highly likely to emerge out of recombinant creation dynamics. Recent efforts to characterize regional knowledge production in terms of degree of novelty are therefore relevant in this respect. In particular, a growing body of the geography of innovation of literature has started enquiring into the determinants of regional differences in the production of pure novelties, or technological breakthroughs, and how these correlate to key geographical dimensions such as city size (Castaldi et al., 2015; Mewes, 2019). These studies identify regional novelty by looking at the co-occurences of technological classes within patent documents issued in the region. It has been found that recombinant novelty, i.e. the appearance of patents showing *atypical* combinations, is associated to knowledge bases characterized by relatively high levels of unrelated variety, and it is more likely to occur in very large cities.

The generation of GTs in local innovation systems is thus not only influenced by the heterogeneity of local knowledge bases but also, and most importantly, by the local availability of competences allowing for the combination of knowledge inputs that are both highly dispersed across the knowledge space and loosely related. Therefore, the presence of recombinant creation capabilities within a region provides a fertile ground to conduct research aiming at generating new technologies for the reduction of environmental risk.

In view of the arguments discussed so far, we formulate the first hypothesis as follows:

H1. The generation of GTs in regional contexts is positively associated with the presence of recombinant creation capabilities.

The concept of capabilities itself implies a process of historical accumulation through experimentation and learning. However, the increasing pressure to improve the environmental performances of economic activities, and the consequent increased stringency of regulatory frameworks, has engendered a sheer increase in the demand for GTs, making their production a

business more and more profitable (Colombelli et al., 2020). Areas with low or no recombinant creation capabilities, where agents are more familiar with the refinement or improvement of known combinations, are likely to be worse off in this context. The identification of factors that may compensate for the local absence of recombinant creation capabilities is important to elaborate local strategies and policies for boosting research and innovation in the green domain. The next Section will introduce the collaboration between industry and universities as a relevant dimension in this respect.

2.3 The involvement of academic inventors

The features of GTs introduced above, together with the clear importance of recombinant creation capabilities, bring the relevance of collective invention dynamics at the core of the discussion. The collaboration among different organizations that are repositories of a variety of specialist knowledge and competences has indeed proven to be a fruitful organizational mode for the generation of GTs (De Marchi, 2012; De Marchi and Grandinetti, 2012). Recent literature has specifically stressed that collaboration with universities is a primary source of comparative advantage in doing research in the GT domain, as it is essential for achieving more radical innovation and relative novel technologies (Cainelli et al., 2012; Triguero et al., 2013; Fabrizi et al., 2018).

Microlevel studies have stressed that the educational attainment of inventors is a key driver of success for collaboration and teamwork knowledge production, especially in science and engineering (Allen, 1984). An extensive literature has shown that inventors with higher educational attainment are more likely to better address technological problem solving; in addition, they are less likely to be locked-in by cognitive constraints and more prone to engage in boundary-spanning activities (March and Simon, 1958; Hambrick and Mason, 1984; Gagné and Glaser, 1987; Walsh, 1995; Pelled, 1996; Hargadon, 2006). A recent study has shown that patents spanning technological boundaries are more likely to be produced by scientists than engineers, concluding that inventors holding a scientific background are better able to command recombinant dynamics across different and unrelated technological domains (Gruber et al. 2013). In line with these arguments, Quatraro and Scandura (2019) show that the involvement of scientists-inventors from academic institutions in patenting activities bear a positive impact on the generation of GTs. In view of their higher level of human capital, as compared to inventors employed in industry, academic inventors are expected to hold the necessary capabilities to recombine knowledge across diverse technological domains, this being a fundamental pre-condition for the creation of environmentally sound inventions.

The development of effective collaborations between university and industry represents therefore a fruitful strategy to increase the likelihood for regional innovation systems to show positive performances in the generation of GTs. Because of their familiarity with recombinant creation dynamics, the local availability of an academic infrastructure well connected with the private sector may compensate for the insufficient development of recombinant creation capabilities in the region.

Following these arguments, we spell out the second hypothesis as follows:

H2. The lower is the level of recombinant creation capabilities in a region, the larger the positive association between the involvement of academic inventors and the local generation of green knowledge.

3 Data, variables and methods

3.1 Data sources

We test our hypotheses on a balanced panel dataset of 103 Italian NUTS 3 regions (corresponding to the Italian *provinces*) observed from 1998 to 2009. Data sources are multiple. First, we collect patent information from the OECD Regpat database, which allows assigning patents to Italian provinces by exploiting information contained in recorded inventor addresses. Moreover, the OECD Regpat dabase provides information on IPC classes classifying EP patents that we use to individuate green technologies. Second, we rely on the "Academic Patenting in Europe" (APE-INV) database to individuate academic inventors in Italy.[3] Third, we collect regional administrative data at NUTS 2 and 3 level from the Cambridge Econometrics European Regional Database. Additional data come from the Italian Institute for National Statistics (ISTAT) and from Legambiente, an Italian environmental no profit association.

3.2 Dependent variable

[3] APE-INV is a project on academic patenting in Europe funded by the European Science Foundation. See Lissoni (2013) and the project website http://archives.esf.org/coordinating-research/research-networking-programmes/social-sciences-soc/current-research-networking-programmes/academic-patenting-in-europe-ape-inv.html

Our dependent variable is the province-level stock of green knowledge generated via green patents. To measure the stock over time, we follow the perpetual inventory method (Peri, 2005; Dechezleprêtre et al., 2015; Bloom and Van Reenen, 2002).

To individuate green patents we exploit the OECD Indicator of Environmental Technologies (OECD, 2011) combined with the OECD Regpat database (Maraut et al., 2008). The OECD Indicator of Environmental Technologies, based on the International Patent Classification (IPC), individuates seven broad environmental areas: (a) general environmental management, (b) energy generation from renewable and non-fossil sources, (c) 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 OECD Regpat database provides direct links between IPC classes and regions according to the addresses of the applicants and inventors. In the Italian case, we exploit information at NUTS 3 level (i.e. provinces).

The rationale behind the decision of using patent-stock variables in our analysis is threefold. First, patent count variables show large fluctuations over time. This volatility leads to econometric issues. In this case, cumulated knowledge provides a more comprehensive picture of the phenomenon at stake, while also accounting for the annual flow of green patents generated. Second, the time lag between patent filing and patent granting (on average 18–24 months for EPO patents, with large variability across technological domains) causes yearly patent counts to be misleading with respect to the actual stock of knowledge generated via patent at a given time. The stock variable instead capitalizes past and currently generated knowledge, attenuating this issue. Additionally, with respect to patent flows, patent stocks allow to account for the fact that the benefits accruing from a patent are persistent over time (Bloom and Van Reenen, 2002).

We measure the province-level stock of green patents applying the recursive formula $GT\_STOCK_{i,t} = (1-d)GT\_STOCK_{i,t-1} + N\_GT_{i,t}$, where $N\_GT_{i,t}$ is the flow of province level patent applications previously defined and d is the decay rate of the stock of past patent applications ($GT\_STOCK_{i,t-1}$). The value chosen for d is 15%, commonly used in the literature (Keller, 2002). We calculate the stock of green patents since 1977, the first filing year for an Italian patent reported in the OECD Regpat database.

3.3 Independent variables

The two main drivers of the accumulation of green knowledge that we focus on in this chapter are the local capacity of combinatorial technological novelty and the local involvement of academic inventors in patenting activities. Both combinatorial novelty and academic involvement refer to domains outside the environmental spectrum. In other words, our aim is to capture some local knowledge spillovers from novelty and academic involvement that is likely to foster the rate of accumulation of green knowledge.

3.3.1 Combinatorial novelty

To measure combinatorial novelty we rely on the co-occurrence of patent IPC classes between citing and cited patents. The rationale for exploiting links between patents and their citations to measure novelty is that patent citations are references to prior technology on which the current patent builds or which it uses, i.e. prior art (Trajtenberg, 1990; Jaffe et al., 1993; Jaffe and Trajtenberg, 1999; Maurseth and Verspagen, 2002). Therefore, if the technology in which the patent is classified relies on a novel bit of prior art, this signals for an original combinatorial attempt that, possibly, enriches the technology space, opening rooms for new technological trajectories (Fleming, 2001). If this mechanism works, the knowledge contained in novel technological attempts is likely to spill over and to contribute to further developments of green technologies. Precisely, we define as novel in recombination a patent that links, for the first time in Italy, a specific IPC class with another IPC (cited, or contained in the patent backward citations).[4] We borrow this measure from Verhoeven et al. (2016) and we adapt it to the Italian context. Therefore, a patent filed in year t shows a novel combination if, from 1977 to $t-1$, the same combination was never observed within Italian patents.[5] Since we are interested in the relationship between local combinatorial novelty in non-green domains and the generation of GTs, we do not consider green IPC classes when measuring combinatorial novelty. To assign novel patents to Italian provinces, we rely on information contained in inventor addresses reported in the OECD Regpat database.[6]

We build two main variables related to local combinatorial novelty in non-green inventions. First, we build an indicator that takes value 1 if the province has at least one patent showing a novel combination between its IPC classes and the IPC classes contained in its backward citations (

[4] We consider 4-digits IPC classes.
[5] A novel combination may appear simultaneously in more than one patent, as well as in more than one province. We take the patent priority year as time reference to assign patents to provinces.
[6] If two or more inventors residing in different provinces sign one patent, the patent is assigned to each province according to the share of inventors residing there as recorded at the time of the patent filing.

$REC\_NOVEL\_d_{i,t}$). This variable has a mean value of 0.67, indicating that around two over three provinces across time (1998-2009) presents at least one patent with combinatorial novelty (see Table 1). Second, we measure the local stock of patents showing novel combinatorial novelty ($REC\_NOVEL\_s_{i,t}$). To measure the latter we follow the same method applied for measuring the local stock of green patents.

3.3.2 Academic inventors

The second driver that we consider is the involvement of academic inventors in local patenting activity. We retrieve information on academic inventors from the APE-INV database.[7] The database collects information on patents filed by academics at the EPO. We restrict the sample to Italian academic inventors (i.e. inventors residing in Italy and working in Italian academic institutions). Accordingly, we assign academic patents to provinces. Precisely, we build two variables related to local academic patenting. The first is an indicator that takes value 1 for provinces with at least one patent filed by an academic inventor, and 0 otherwise ($ACAD\_PAT_{i,t}$). $ACAD\_PAT_{i,t}$ has a mean value of 0.47, indicating that 47% of provinces across time (1998-2009) presents academic patenting activity (see Table 2). Second, we compute the stock of patents involving academic inventors ($ACAD\_STOCK_{i,t}$). The stock is calculated following the same methods used for measuring both GT_STOCK_{it} and $ACAD\_STOCK_{it}$.

3.3.3 Control variables

We include a vector of control variables in our empirical specification to account for socio-economic and technological factors likely to explain green patenting at the NUTS 3 level. First, we control for the overall local non-green, non-novel and non-academic patenting intensity. Accordingly, we build a measure of per capita stock of patents at the province-level ($PC\_STOCK\_NG_{i,t}$).[8] Second, we control for industry related factors such as industry gross value added ($IND\_GVA_{i,t}$) and employment in industry ($IND\_EMP_{i,t}$). Local propensity to patent

[7] Reliable data on Italian academic inventors cover the period 1996–2009. In this paper, we shorten it to 1998–2009, for which we have complete information on all other variables.

[8] We measure this variable as the ratio between the stock of patents filed in the province and the active population (in thousands). This patent stock, calculated the same way as done for green, novel and academic patents, does not include green, novel and academic patents.

(both in green and non-green domains) is in fact shaped by the overall level of industrial activities. The data source of these variables is the Cambridge Econometrics' European Regional Database (ERD). We control for total R&D expenditures ($R\&D\_PROV_{i,t}$) and for the number of graduates in science and technology fields ($S\&T\_GRAD_{i,t,}$) to capture, respectively, the determinants of GTs related to local R&D monetary efforts and local availability of skilled workforce (human capital). These two variables come from ISTAT, that provides them at the NUTS 2 level. To compute the provincial corresponding values, we weigh the NUTS 2 value for the NUTS 3 share of regional GDP. Third, we also control for the local heterogeneity of technological domains to account for the structure of the local technological base. To do so, we build a measure of local technological variety, based on the co-occurrence frequency of IPC classes within patent applications at the NUTS 3 level.[9] The higher the value of this variable ($TECH\_VAR_{i,t}$), the higher the technological variety in a given province. As widely stressed by previous scholars, local variety proxies Jacob's knowledge externalities, i.e. external effects due to diversification of technological activities, instead of agglomeration and specialization (Antonelli et al., 2011, 2017). Therefore, this variable grasps the importance of the recombination of a wide array of heterogeneous technologies for the generation of GTs. Moreover, the level of local variety is also likely to affect the likelihood of the occurrence of combinatorial novel attempts.

Finally, to control for the impact of environmental policies we follow a common approach in the literature and we implement an indirect measure (Costantini and Crespi, 2008; OECD, 2011). Precisely, we use the index of urban environmental quality proposed by the Italian non-profit organization Legambiente. The Legambiente's index evaluates and ranks the 103 province-capital cities in Italy, based on several indicators of e.g. air quality, green areas, drinking water quality, energy consumption, and waste recycling performance. This ranking provides an implicit assessment of the performance of local policy-makers in managing environmental protection tasks (Bianchini and Revelli, 2013).[10] According to this index, we build an indicator of environmental policy stringency ($D\_ECO_{i,t,}$) that takes value one if the province is above the national annual median, zero otherwise. The Legambiente's index is available since 2001.

Tables 1 and 2 report the variables description and the summary statistics, respectively. Table 3 presents the correlation between variables.

[9] 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.

[10] For an accurate description of the Legambiente's index and for a complete discussion about the opportunity of its implementation in empirical contexts such the one proposed in this study, please see Quatraro and Scandura (2019).

[TABLE 1 AND TABLE 2 AROUND HERE]

3.4 Empirical methodology

The literature dealing with the empirical analysis of regional innovation performances relies often on the implementation of the so-called knowledge production function (KPF), a pillar of applied studies in economics of innovation (Griliches, 1979, 1990, 1991; Romer, 1990; Link and Siegel, 2007). Following and extending previous works, we employ an enriched KPF where the stock of green patents (GT_STOCK_{it}) is the dependent variable and the local capacity in combinatorial novelty ($REC\_NOVEL\_d_{i,t}$ or $REC\_NOVEL\_s_{it}$), academic inventors' involvement ($ACAD\_s_{i,t}$ or $ACAD\_d_{it}$), and their interactions are among the regressor of main interest. Moreover, we include a vector of control variables ($X'_{i,t}$) as described in Section 3.3.3, NUTS 2 fixed effects (ρ_i) and year fixed effects (τ_t). Formally, we estimate four main models:

$$GT\_STOCK_{i,t} = \beta_0 + \beta_1 REC\_NOVEL\_d_{i,t-2} + \beta_2 ACAD\_d_{i,t-2} + \beta_3 REC\_NOVELd_{i,t-2} \times ACAD_{i,t-2} + X'_{i,t-1} + \rho_i$$

(1)

$$GT\_STOCK_{i,t} = \beta_0 + \beta_1 REC\_NOVEL\_s_{i,t-2} + \beta_2 ACAD\_d_{i,t-2} + \beta_3 REC\_NOVEL\_s_{i,t-2} \times ACAD_{i,t-2} + X'_{i,t-1} + \rho$$

(2)

$$GT\_STOCK_{i,t} = \beta_0 + \beta_1 REC\_NOVEL\_d_{i,t-2} + \beta_2 ACAD\_s_{i,t-2} + \beta_3 REC\_NOVEL\_d_{i,t-2} \times ACAD\_s_{i,t-2} + X'_{i,t-1}$$

(3)

$$GT\_STOCK_{i,t} = \beta_0 + \beta_1 REC\_NOVEL\_s_{i,t-2} + \beta_2 ACAD\_s_{i,t-2} + \beta_3 REC\_NOVEL\_s_{i,t-2} \times ACAD\_s_{i,t-2} + X'_{i,t-1} +$$

(4)

where $REC\_NOVEL\_d_{i,t-2}$ and $ACAD\_d_{i,t-2}$ are the yes/no dummies, while $REC\_NOVEL\_s_{i,t-2}$ and $ACAD\_s_{i,t-2}$ are the variables calculated as stocks.

In our sample, 11% of the year-province observations show zero green patents. If the observed zeros are due to the absence of local patenting activity, this can lead to well-known econometric issues. Zero-inflated negative binomial (ZINB) models are the most appropriate solution in these cases. ZINB allows the zeros and the positive values of the dependent variable to be generated by different processes. In fact, the ZINB model runs two equations simultaneously: a binary logistic equation to model the zeros (the inflation part of the model) and a negative binomial equation to model the dependent variable. The former equation allows differentiating between

provinces with overall patenting activity but not green patents and provinces with null patenting activity. We base the inflation model on the stock of total patents (both green and non-green) in each province ($K\_TOT_{i,t}$).

In order to exploit the panel structure of the data, we also include year and region fixed effects. We include NUTS 2 fixed effects to allow the analytical convergence of the ZINB model and we cluster standard errors at NUTS 3 level so to account for province-specific effects. In addition, we lag the regressors to mitigate reverse causality concerns. Precisely, we lag the vector of control variables by one year and the variables related to combinatorial novelty and academic patenting by two years. Finally, given the skewness of some of the continuous variables, we transform them to linearize their trend. We apply the inverse hyperbolic sine transformation to all continuous variables, which allows not losing any zero in the variables.[11]

4 Results

4.1 Main results

The results of the main estimations are reported in Table 3, where both the measures of recombinant creation capabilities and the involvement of academic inventors are implemented as dummy variables.[12]

Columns (1) to (3) present models alternating our focal regressors. In column (1) we observe that the *REC_NOVEL_d* variable shows positive and significant coefficients, providing support to the first hypothesis of this work: the local availability of capabilities to produce atypical and unprecedented combinations of knowledge inputs is associated with positive performances of regional innovation systems in the generation of green technologies. In column (2) we include the *ACAD_d* dummy variable. In line with Quatraro and Scandura (2019), the coefficient is positive and significant, hence supporting the argument that the involvement of academic inventors in patenting activity is associated to better performances in terms of the production of technologies in the green domain. The estimates in column (3) includes both regressors of interest (*REC_NOVEL_d* and

[11] This is an alternative to the Box-Cox transformations, defined by the following formula: inverse_y=log[yi+(yi2+1)12]. 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 and Magee, 1990).

[12] It is worth stressing that our results can by no means be interpreted as causal relationships. Our empirical setting allows us to interpret our findings in terms of empirical associations.

ACAD_d) and show persistency and robustness in the results as the coefficients are positive and significant (at 1% level)

In order to test our second hypothesis, we include the interaction term *REC_NOVEL_d*ACAD_d* in column (4), so to ascertain whether the involvement of academic inventors at the local level may compensate for the lack of recombinant creation capabilities that the province shows. The coefficient of the interaction variable is negative and significant, thereby confirming such compensation effect. In other words, academic inventors show their larger effectiveness in areas where recombinant capabilities are scarce. Finally, in column (5) we show the results of the fully specified model, where we also add the measure of environmental policies *D_ECO*. We do not observe any sizeable change in the results.

>>> INSERT TABLE 3 ABOUT HERE <<<

As for the control variables, in line with an increasing body of literature, the variable employed to measure potential spillovers from non-green technologies shows positive and significant coefficients. This suggests that hybridization across different technologies outside the green domain is a lever for the development of GTs (Zeppini et al., 2011; Dechezleprêtre et al., 2013; Montresor and Quatraro, 2019; Quatraro and Scandura, 2019). The coefficients of the share of employment in the manufacturing sector (*IND_EMP*) and the graduates in science and technology disciplines (*S&T_GRAD*) show not statistically significant coefficients. As for the science-push dynamics, the coefficient of the total levels of R&D expenditure (*R&D_PROV*) is positive and significant as expected (Costantini et al., 2015). Finally, we investigate the role of technological variety in terms of recombination of knowledge components, i.e. technological classes. Consistently with the arguments presented in Section 2, the coefficient of this variable is positive and significant, suggesting that it is more likely to observe high levels of GTs production in areas characterized by high heterogeneity in the recombinant dynamics underpinning local knowledge bases.

In table 4, we replicate the regressions presented in table 3 using the variable *REC_NOVEL_s* measuring the local *stock* of patent drawing on recombinant creation. Its coefficients along with that of the dummy *ACAD_d* are positive and significant, thus confirming the hypothesized relationships. This holds when they are included both separately and jointly in the regressions. In the latter case, the first hypothesis finds large support (see column (3)). The more the stock of local knowledge relies on atypical and unprecedented combination of knowledge inputs, the higher the local productivity of GT patents.

In column (4) we add the interaction term *REC_NOVEL_s*ACAD_d.* The coefficient of the interaction variable is negative and significant. When the dummy variable *ACAD_d* is equal to 1, the impact of recombinant creation capabilities is sensibly mitigated, suggesting the existence of the hypothesized compensation effect. In column (5) we plug in the variable controlling for the role of environmental policies and we obtain very similar results to those of column (4). As for the vector of control variables, the results are comparable to those presented in table 3, with the only exception of the coefficients of *PC_STOCK_NG*, which is not significant in some of the estimates.

>>> INSERT TABLE 4 ABOUT HERE <<<

In table 5 we run a set of estimations that include both the stock of patents drawing on recombinant creation dynamics and the stock of academic patents. Results are stable as far as the *REC_NOVEL_s* variable is concerned. The *ACAD_s* is positive and statistically significant only when included along with the interaction term in column (4). This latter shows the expected negative and significant coefficient. In column (5), the estimations including the measure of environmental policies confirm the results shown in column (4).

Overall, this first set of estimations provides robust support to our empirical hypotheses, according to which local innovation systems showing good capabilities in the recombination of knowledge components never combined before show better performances in terms of GT generation. Moreover, the involvement of academic inventors in patenting activity is not only positively associated to inventions in the green domain, but also appears to compensate for the lack of familiarity of local agents with recombinant creation dynamics.

[TABLE 5 ABOUT HERE]

4.2 Robustness checks

We implement two robustness checks of our results, where we include a dummy variable, *NO_REC_NOVEL_d*, taking value one for NUTS 3 regions characterized by below the national median level of the stock of patents drawing on recombinant creation (i.e. provinces with scarce combinatorial capabilities). We perform these tests to provide further robust evidence of the expected compensation effect between academic involvement and local combinatorial capabilities. According to the results discussed in the previous section, local areas with high recombinant capabilities are more likely to generate GTs. Since the indicator we use in this first set of robustness checks takes value one for local areas characterized by low levels of combinatorial capability, we expect to observe an associated negative and significant coefficient for this indicator. Importantly,

following the argument (and the evidence shown in the previous section) we do expect to observe compensation driven by academic inventors when combinatorial capabilities are weak. Therefore, our expectation is to observe the largest contribution of academic inventors to the generation of GTs when *NO_REC_NOVEL_d* is equal to one. In other words, our expectation is that the coefficient for the interaction between *NO_REC_NOVEL_d* and *ACAD_d* will be positive and significant.

In table 6 we include the dummy *NO_REC_NOVEL_d* along with the dummy variable *ACAD_d*. Columns (1) to (3) alternate our focal regressors to check their individual effects. Consistently with the arguments spelt out in Section 2 and with our main results, the coefficient for *NO_REC_NOVEL_d* is negative and significant, supporting the hypothesis that recombinant capabilities matter for triggering the generation of GTs in local innovation systems. The dummy *ACAD_d* shows a positive and significant coefficient, in line with extant evidence on the role of academic inventors in green patenting and with the main results of this work.

We introduce the interaction term *NO_REC_NOVEL_d *ACAD_d* in column (4) and its coefficient is positive and significant. This provide supportive evidence of our second hypothesis according to which the impact of the involvement of academic inventors in green patenting is magnified in contexts featured by low levels of recombinant creation capabilities. Column (5) presents the results of the full model, showing their overall robustness.

>>> INSERT TABLE 6 ABOUT HERE <<<

In table 7 we employ both the newly created *NO_REC_NOVEL_d* and the stock variable *ACAD_s*. The results are in line with our previous estimations. In particular, *NO_REC_NOVEL_d* shows negative and significant coefficients in all of the estimated models. However, the coefficient of *ACAD_s* is only weakly significant in one of the models. Columns (4) and (5) present the full model, and show that the coefficients of the regressors of interest are very similar to those in our previous estimations. In particular, the impact of academic inventors is larger in regions showing low levels of recombinant creation capabilities than in regions where innovating agents are experienced with recombinant efforts across diverse and loosely related areas of the knowledge space.

>>> INSERT TABLE 7 ABOUT HERE <<<

5 Conclusions

In this paper we have investigated the impact of region-level recombinant creation capabilities on the capacity of local innovation systems to successfully engage in the generation of GTs. Moreover, we have considered the role of university-industry collaborations in compensating for the lack of these capabilities in local contexts. We have developed a theoretical framework grounded on the recombinant knowledge approach and its recent application to the analysis of the antecedents of GTs. In this framework, theoretical and empirical studies have stressed that GTs are on average more complex than non-green technologies, and that patenting activities in the green domain are favoured by the capacity to combine technologies that are loosely related to one another (Zeppini et al., 2011; Barbieri et al., 2020; Orsatti et al., 2020a). Accordingly, we have hypothesized that the local accumulation of innovation capabilities based on the implementation of atypical and unprecedented combination of knowledge components may be crucial for the success of innovation dynamics in the green domain. On similar grounds, we have followed the stream of literature on university-industry collaboration, which stresses the advantages of involving scientists from academic institutions in inventor teams. These advantages are related to the educational attainment of academic inventors and the related higher likelihood to be able to command boundary-spanning exploratory research leading to combinations of knowledge components from dispersed areas of the knowledge space (Quatraro and Scandura, 2019).

The analysis has focused on the generation of GTs in Italian NUTS 3 regions, over the period 1998-2009. Our results provide evidence of empirical associations between the development of local recombinant creation capabilities and the generation of GTs. This result is robust to different econometric specifications. In addition, the impact of the involvement of academic inventors in patenting activities is magnified in areas characterized by low or no presence of those capabilities,.

As any empirical study, this one is not free from limitations, mostly related to the use of patents to proxy for technological efforts and to the measurement of university-industry interactions with the involvement of academic researchers in inventor teams. One issue is that not all innovations involve the introduction of new technologies. This is the reason why we restrict our arguments to the generation of GTs, which are a subset of the broad family of eco-innovations. Second, new invented technologies are not always patented. However, despite their limitations, patents have been extensively used in the literature dealing with eco-innovation dynamics (Barbieri et al., 2016) and, in general, there is large scientific agreement that they are a reliable indicator of the generation of new technologies, especially at the local level (Acs et al., 2002). Moreover, extant literature has stressed the crucial importance of academic inventors for regional patenting activities

(see e.g. Meyer et al., 2003; Murray, 2004; Lissoni, 2010). Lastly, our empirical framework does not allow us to gain knowledge on causal relationships. Therefore, while showing strong statistical associations, our results must be interpreted with caution.

Yet, this paper contributes the literature attempting to open the black box of green technologies, as it unveils knowledge dynamics and related innovation capabilities behind their generation. Firstly, we contribute the literature on the regional antecedents of GTs, by elaborating upon the role of recombinant capabilities. Secondly, and related to the previous point, we make a step forward in the consideration of recombinant dynamics behind the generation of GTs, by leveraging the concept of novelty in the combination of knowledge components to invent new technologies (Castaldi et al., 2015). Third, we add to the literature on the role of inventors in local patent dynamics. Drawing upon the literature stressing the peculiarities of inventors in recombination dynamics (e.g. Gruber et al., 2013), we show that there are compensation effects between the accumulation of recombinant creation capabilities at the local level and the involvement of academic inventors in patenting activities.

Our results bear interesting policy implications for the elaboration of successful regional strategies to promote research and innovation in the green domain, in view of the increasing commitment at the European level to cope with climate change and achieve decarbonized societies. Environmental innovations in general and green technologies in particular, represent a key lever that will allow to comply with the objectives of the European Green Deal, as well as their articulation at the regional level in EU Cohesion Policies. Regions characterized by a well-established innovation system specialized in research and innovation activities dealing with complex technologies and based on exploration dynamics will be better off in this respect. However, strengthening the institutional framework conducive to successful collaborations between industry and universities might be an alternative strategy for regions that features innovation dynamics mostly focused on incremental improvements of known technologies, with scarce impact on the advancement of the knowledge frontier.

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7 Tables and Figures

Table 1 - Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
GT_STOCK	1,236	2.426	1.532	0	6.761
REC_NOVEL_d	1,236	.678	.467	0	1
REC_NOVEL_s	1,236	2.093	1.555	0	6.163
ACAD_d	1,236	.468	.499	0	1
ACAD_s	1,236	.969	1.205	0	5.433
PC_STOCK_NG	1,236	.161	.187	0	1.257
IND_EMP	1,236	4.138	.956	1.875	6.902
S&T_GRAD	1,236	2.502	.955	0	3.684
R&D_PROV	1,236	11.952	.994	8.352	15.388
TECH_VAR	1,236	2.005	.757	0	2.940
D_ECO	927	.494	.500	0	1

Table 2 - Correlation Matrix. N=1,236

		1	2	3	4	5	6	7	8	9	10	11
1	GT_STOCK	1										
2	NOVEL_d	0.58	1									
3	NOVEL_s	0.85	0.69	1								
4	ACAD_d	0.48	0.36	0.46	1							
5	ACAD_s	0.60	0.37	0.58	0.64	1						
6	PC_STOCK_NG	0.63	0.44	0.76	0.29	0.38	1					
7	IND_EMP	0.76	0.55	0.79	0.48	0.55	0.46	1				
8	S&T_GRAD	0.40	0.26	0.41	0.18	0.27	0.43	0.19	1			
9	R&D_PROV	0.80	0.50	0.76	0.49	0.60	0.45	0.82	0.38	1		
10	TECH_VAR	0.67	0.57	0.70	0.42	0.46	0.49	0.70	0.26	0.66	1	
11	D_ECO	0.22	0.25	0.28	0.12	0.11	0.31	0.20	0.26	0.12	0.29	1

*Table 3 - ZINB regressions. Independent variables: REC_NOVEL_d, ACAD_d, REC_NOVEL_d*ACAD_d.*

	(1)	(2)	(3)	(4)	(5)
REC_NOVEL_d	0.188***		0.181***	0.251***	0.222***
	(0.000)		(0.000)	(0.000)	(0.000)
ACAD_d		0.0965***	0.0873***	0.251***	0.265***
		(0.003)	(0.004)	(0.004)	(0.002)
REC_NOVEL_d*ACAD_d				-0.192**	-0.205**
				(0.026)	(0.014)
PC_STOCK_NG	0.346**	0.354**	0.341**	0.352**	0.441***
	(0.021)	(0.021)	(0.018)	(0.015)	(0.004)
IND_EMP	-0.0598	-0.0441	-0.0544	-0.0557	-0.0322
	(0.445)	(0.581)	(0.483)	(0.471)	(0.698)
S&T_GRAD	-0.0656	-0.0461	-0.0735	-0.0737	0.00582
	(0.399)	(0.562)	(0.342)	(0.342)	(0.951)
R&D_PROV	0.329***	0.307***	0.305***	0.312***	0.283***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TECH_VAR	0.307***	0.332***	0.291***	0.275***	0.246***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
D_ECO					0.0285
					(0.282)
N	1236	1236	1236	1236	927
AIC	3533.6	3538.7	3532.1	3531.3	2717.2
BIC	3738.4	3743.5	3742.0	3746.3	2910.4
Log Lik	-1726.8	-1729.4	-1725.0	-1723.6	-1318.6
McFadden's R2	0.233	0.232	0.234	0.234	0.221

p-values in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

Table 4 - Baseline regressions, stock novelty, dummy academics

	(1)	(2)	(3)	(4)	(5)
REC_NOVEL_s	0.126***		0.124***	0.165***	0.120***
	(0.002)		(0.002)	(0.000)	(0.009)
ACAD_d		0.0965***	0.0918***	0.337***	0.334***
		(0.003)	(0.003)	(0.000)	(0.000)
REC_NOVEL_s*ACAD_d				-0.0946***	-0.0897***
				(0.001)	(0.002)
PC_STOCK_NG	0.0373	0.354**	0.0378	0.126	0.320**
	(0.807)	(0.021)	(0.796)	(0.358)	(0.035)
IND_EMP	-0.0999	-0.0441	-0.0939	-0.106	-0.0722
	(0.204)	(0.581)	(0.228)	(0.168)	(0.393)
S&T_GRAD	-0.0551	-0.0461	-0.0651	-0.0686	0.0244
	(0.472)	(0.562)	(0.395)	(0.363)	(0.799)
R&D_PROV	0.250***	0.307***	0.226***	0.279***	0.280***
	(0.001)	(0.000)	(0.002)	(0.000)	(0.000)
TECH_VAR	0.304***	0.332***	0.286***	0.242***	0.221***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
D_ECO					0.0344
					(0.175)
N	1236	1236	1236	1236	927
AIC	3532.2	3538.7	3530.3	3522.8	2713.7
BIC	3737.0	3743.5	3740.2	3737.8	2907.0
Log Lik	-1726.1	-1729.4	-1724.2	-1719.4	-1316.9
McFadden's R2	0.233	0.232	0.234	0.236	0.222

p-values in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

Table 5 - Baseline regressions, stock novelty, stock academics

	(1)	(2)	(3)	(4)	(5)
REC_NOVEL_s	0.126***		0.125***	0.151***	0.109**
	(0.002)		(0.002)	(0.000)	(0.010)
ACAD_s		0.0295	0.0265	0.189***	0.180***
		(0.105)	(0.153)	(0.000)	(0.000)
REC_NOVEL_s*ACAD_s				-0.0427***	-0.0381***
				(0.000)	(0.000)
PC_STOCK_NG	0.0373	0.326**	0.0121	0.178	0.343**
	(0.807)	(0.037)	(0.934)	(0.172)	(0.019)
IND_EMP	-0.0999	-0.0294	-0.0812	-0.0958	-0.0564
	(0.204)	(0.718)	(0.308)	(0.218)	(0.511)
S&T_GRAD	-0.0551	-0.0465	-0.0647	-0.0582	0.00993
	(0.472)	(0.560)	(0.399)	(0.462)	(0.914)
R&D_PROV	0.250***	0.284***	0.207***	0.279***	0.263***
	(0.001)	(0.000)	(0.006)	(0.000)	(0.001)
TECH_VAR	0.304***	0.344***	0.297***	0.199***	0.177***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.005)
D_ECO					0.0194
					(0.432)
N	1236	1236	1236	1236	927
AIC	3532.2	3541.4	3533.0	3516.4	2709.4
BIC	3737.0	3746.2	3742.9	3731.5	2902.6
Log Lik	-1726.1	-1730.7	-1725.5	-1716.2	-1314.7
McFadden's R2	0.233	0.231	0.234	0.238	0.223

p-values in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

Table 6 - Baseline regressions, dummy novelty (below median), dummy academics

	(1)	(2)	(3)	(4)	(5)
NO_REC_NOVEL_d	-0.156**		-0.149**	-0.245***	-0.206**
	(0.015)		(0.016)	(0.002)	(0.016)
ACAD_d		0.0965***	0.0901***	0.0243	0.0157
		(0.003)	(0.003)	(0.473)	(0.641)
NO_REC_NOVEL_d*ACAD_d				0.198***	0.210***
				(0.008)	(0.006)
PC_STOCK_NG	0.278**	0.354**	0.276**	0.289**	0.401***
	(0.037)	(0.021)	(0.032)	(0.023)	(0.003)
IND_EMP	-0.0681	-0.0441	-0.0625	-0.0592	-0.0363
	(0.384)	(0.581)	(0.419)	(0.436)	(0.653)
S&T_GRAD	-0.0537	-0.0461	-0.0621	-0.0678	0.0221
	(0.494)	(0.562)	(0.428)	(0.384)	(0.822)
R&D_PROV	0.329***	0.307***	0.304***	0.308***	0.283***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TECH_VAR	0.315***	0.332***	0.298***	0.279***	0.256***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
D_ECO					0.0329
					(0.230)
N	1236	1236	1236	1236	927
AIC	3536.6	3538.7	3534.8	3531.9	2717.7
BIC	3741.3	3743.5	3744.7	3746.9	2910.9
Log Lik	-1728.3	-1729.4	-1726.4	-1723.9	-1318.8
McFadden's R2	0.232	0.232	0.233	0.234	0.221

p-values in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

Table 7 - Baseline regressions, dummy novelty (below median), stock academics

	(1)	(2)	(3)	(4)	(5)
NO_REC_NOVEL_d	-0.156**		-0.156**	-0.283***	-0.242***
	(0.015)		(0.014)	(0.000)	(0.005)
ACAD_s		0.0295	0.0297*	0.0133	0.0184
		(0.105)	(0.090)	(0.451)	(0.282)
NO_REC_NOVEL_d*ACAD_s				0.152***	0.145***
				(0.000)	(0.001)
PC_STOCK_NG	0.278**	0.326**	0.244*	0.299**	0.395***
	(0.037)	(0.037)	(0.059)	(0.019)	(0.004)
IND_EMP	-0.0681	-0.0294	-0.0482	-0.0375	-0.00812
	(0.384)	(0.718)	(0.540)	(0.626)	(0.922)
S&T_GRAD	-0.0537	-0.0465	-0.0637	-0.0590	0.0175
	(0.494)	(0.560)	(0.417)	(0.453)	(0.850)
R&D_PROV	0.329***	0.284***	0.279***	0.276***	0.237***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)
TECH_VAR	0.315***	0.344***	0.307***	0.244***	0.215***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
					0.0246
					(0.356)
N	1236	1236	1236	1236	927
AIC	3536.6	3541.4	3536.9	3527.5	2714.2
BIC	3741.3	3746.2	3746.8	3742.5	2907.5
Log Lik	-1728.3	-1730.7	-1727.5	-1721.8	-1317.1
McFadden's R2	0.232	0.231	0.233	0.235	0.222

p-values in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$