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Regional patterns of unrelated technological diversification: the role of academic inventors

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Abstract

This paper investigates the relationship between the involvement of academic inventors in local innovation dynamics and the patterns of regional technological diversification. Based on the combination of the evolutionary economic approach and the theories on regional innovation capabilities, and on the distinctive features of academic inventors, we hypothesise that knowledge spillovers accruing from the participation of university scientists to local patenting activity influence the extent of regional technological diversification. In addition, we posit that the involvement of academic inventors mitigates the path dependency engendered by the constraining role of the existing capabilities. The empirical results highlight the key role of academic institutions for the development of regional technological trajectories while contributing to the academic and policy debate on regional diversification strategies.

Keywords: regional diversification, relatedness, academic inventors
Jel codes: O33, R11

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1 Introduction

Scholars in economic geography have shown rapidly growing interest in the ways regions activate new development patterns and in the reasons why regions differ in their ability to do that (Boschma et al., 2017). The bulk of empirical studies have focused on the process of related diversification and regional branching, showing that existing local capabilities condition which new activities are more likely to develop in regions.[1] These studies conclude that relatedness is an important driver of regional diversification and, as a matter of fact, they find that related diversification is the most dominant pattern in many regions (Boschma, 2017; Xiao et al., 2018).

While regions display a clear tendency to diversify into related activities, it is argued that unrelated diversification is important to secure long-term economic development, since the process of related diversification might eventually come to a halt due to lock-in effects (Saviotti and Frenken, 2008). The pursue of diversification strategies firmly based on the entry in related activities can in fact be dangerous in presence of negative sector-wide performances, due either to structural change or short-term fluctuations. Therefore, the capacity to enter in new and unrelated activities might prove to be a key asset for regions willing to activate long-term development patterns. Unrelated diversification is likely to ensure enduring economic growth and decreasing unemployment (Frenken et al., 2007; Davies and Tonts, 2010; Neffke et al., 2018). As a consequence, understanding the factors that help regions to develop the capacity to diversify in loosely related activities becomes of paramount importance and, it follows, attention for related diversification should go hand in hand with attention for unrelated diversification.

The few existing investigations stress the role of market institutions, foreign firms, and specialization in cross-cutting technologies in engendering regional structural change in mitigating the constraing impact of relatedness (Boschma and Capone, 2015; D'Ambrosio et al., 2019; Montresor and Quatraro, 2017; Neffke et al., 2018). Yet, other factors may be relevant in this context. Notably, while the contribution of academic institutions to local economic development is unquestionable, its role for regional diversification trajectories remains an open issue in the literature (Tanner, 2014). This work intends to shed lights on this issue and aims at extending the stream of the economic geography literature dedicated to the study of regions' diversification strategies in two directions. In the first place, we investigate whether and to what extent academic knowledge spillovers deriving from the participation of university-based inventors into local patenting activity influence regional patterns of technological diversification. Secondly, we assess whether the involve-

[1] Berge and Weterings (2014); Boschma et al. (2015, 2014, 2013); Colombelli et al. (2014); Essletzbichler (2015); Feldman et al. (2015); Heimeriks and Balland (2015); Kogler et al. (2013); Neffke et al. (2011); Rigby (2015); Tanner (2014)

ment of academic inventors influences the impact of technological relatedness on regional diversification trajectories.

The theoretical underpinning of our arguments is twofold. On the one hand, our hypotheses rest on the theory of regional diversification proposed by Boschma et al. (2017); Boschma (2017), according to which, when investigating regional patterns of diversification, one should also account for processes of unrelated diversification by looking at enabling and constraining factors at various spatial scales. We extend this framework so to include the well-known and documented argument on the substantial contribution of universities to territorial economic development (see e.g. Varga, 2000; Ponds et al., 2010), this being an issue that has never been tested on regional diversification patterns (Tanner, 2014). On the other hand, we rely on the conceptualization of novelty creation as the outcome of the recombination of heterogeneous and dispersed knowledge components (Weitzman, 1998; Fleming and Sorenson, 2004; Saviotti, 2007) and on the well-acknowledged assumption that the inputs of such combinatorial activity can hardly be concentrated in one single individual.Crucially, we rely on the documented empirical evidence that academic inventors possess peculiar knowledge sets and cognitive abilities that allow them to be more open toward innovation and to successfully manage the knowledge recombination process across different and unrelated technological domains (see e.g. March and Simon, 1958; Gagné and Glaser, 1987; Walsh, 1995; Gruber et al., 2013).

We test empirically the effect of knowledge spillovers transmitted by academic inventors on the entry of regions in new technological domains; specifically, we will consider the yearly amount of new specialisations entered by regions as our outcome variable. Additionally, we hypothesize that the involvement of academic inventors in local patenting activity mitigates the impact of relatedness on the entry of regions in new technological specializations, hence limiting the path dependency from local capabilities. The empirical investigation focuses on the Italian NUTS 3 regions over the period 1998-2008 and relies on the combination of different data sources, including the OECD RegPat Database, the Academic Patenting in Europe (APE-INV) dataset, the Cambridge Econometrics European Regional Database and the Italian National Institute for Statistics (Istat). We test our hypotheses via linear models in a panel data setting. We also develop spatial panel data regressions to account for spatial effects.

Our results show that academic inventors positively contribute to the extent of regions' entry in new technological domains, measured with the amount of new specialisations developed at the local level; and that their participation to patenting activity reduces the impact of technological relatedness on technological diversification. These findings contribute to the extant literature, particularly to the economic geography strand of literature that considers the role of relatedness and unrelatedness for regional development patterns. Our findings also yield important implications for regional policies aiming at promoting smart specialization strategies oriented towards long-term economic development.

The remainder of the paper is organised as follows: in section 2 we discuss the literature on related and unrelated technological diversification along with that concerned with the role of universities for local economic development; we then develop our empirical hypotheses on the role of knowledge spillovers and university-based inventors; in section 3 we present the data and the methodology used for the econometric analysis; in section 4 we provide evidence about the characteristics of inventions developed by academic inventors; in section 5, we show and describe the results from the econometric analysis, including a set of robustness checks; finally, we present our concluding remarks and policy implications in section 5.

2 Literature and hypotheses development

2.1 Related and unrelated regional diversification in regional branching

The study of the dynamics of regional branching has gained momentum in the last decade. Based on the product space approach elaborated by Hidalgo et al. (2007), evolutionary economic geographers have proposed that regions' development trajectories are shaped by a branching process according to which new specializations in local areas spin out from the existing ones (Boschma and Frenken, 2011; Frenken and Boschma, 2007).

Former investigations have focused on the dynamics behind industrial diversification, showing that regions are more likely to diversify their specializations portfolio by entering into new sectors that are related to the existing ones. The main idea is that workers' intersectoral mobility is more likely to take place between activities that rely on similar or related capabilities. Hence relatedness emerges as the main predictor of the direction of regional diversification patterns (Boschma et al., 2013; Neffke et al., 2018).

On similar grounds, a stream of literature has emerged focusing on the patterns of regional technological diversification (Colombelli et al., 2014; Rigby, 2015). The theory of regional technological branching is grounded on the extension of the recombinant knowledge approach to the regional domain (Fleming, 2001; Fleming and Sorenson, 2004; Weitzman, 1998). Accordingly, the generation of new technological knowledge in local contexts is the outcome of the combination of a variety of knowledge inputs, so that a region's knowledge base is understood as a web of connected elements (Quatraro, 2010). The entry in new technological domains is accordingly the result of the capacity to recombine new knowledge inputs. Learning dynamics and the historical process of local accumulation of capabilities make recombinant dynamics easier to take place in domains in which local agents have already developed sound experience. Relatedness therefore also emerges as a driver of regional technological diversification (Colombelli et al., 2014; Montresor and Quatraro, 2017).

Recent literature has started enquiring into the desirability of relatedness-driven dynamics of industrial diversification. Indeed, the path-dependent dynamics engendered by relatedness might cause lock-in of local development trajectories, due to the associated limited capacity to activate diversification strategies able to cope with critical economic events. Based on these arguments, evolutionary scholars have stressed the importance of unrelated diversification for long-term development strategies (Saviotti, 1996; Saviotti and Frenken, 2008).

Despite the established results about the role relatedness in regional diversification, recent studies have focused on the local conditions that can enable entry in industrial activities that do not match the existing capabilities, hence mitigating the role of relatedness. These former research efforts have looked at the role of external, or non-local actors, like multinational corporations and non-local entrepreneurs (Boschma et al., 2017; Neffke et al., 2018; Elekes et al., 2018; Colombelli et al., 2016; Trippl et al., 2018).

The combination of loosely related knowledge inputs is crucial also for technological diversification, as it enables to open up radically new technological trajectories and introduce valuable innovations (Nightingale, 1998). Diversifying by entry in new technological domains that are loosely related to the existing set of local capabilities can therefore be important to restore the conditions for innovation-based long-term regional growth and competitiveness. Local dynamic capabilities, i.e. the capacity to reconfigure the local set of capabilities, should allow innovation agents to explore a wide array of different technological domains (Quatraro, 2009).

The role of university research in general, and academic inventors in particular, has been much neglected in this context. Yet, they represent an important resource for the development of local innovation capabilities (Varga, 2000; Ponds et al., 2010). In the next Sections we articulate a discussion on their role both in the process of regional technological branching, and in the emergence of technological specialization that are loosely related to the existing activities.

2.2 Universities and regional branching

While studies on regional branching often overemphasize the role of industrial actors and the linkages between industries, the literature has paid very little attention to the role of non-economic actors such as universities (Boschma, 2017; Tanner, 2014). Yet, academic knowledge has been extensively shown to play a key role at the regional level, particularly in the case of complex, knowledge intensive emerging industries (Zucker et al., 1998; Audretsch, 2001). Therefore, the role of knowledge-producing actors like universities and research institutes in the process of regional technological diversification should be critically considered (Tanner, 2014).

The conceptualization of the role of universities in innovation dynamics has evolved over time (Gunasekara, 2006). Former contributions highlighted the role of universities as providers of the scientific knowledge base underpinning industrial innovation (Hart, 1998). The literature on regional innovation systems stresses the importance of localized interactions amongst a variety of institutional actors for the development of regional technological trajectories (Autio, 1998; Braczyk et al., 1998; Cooke, 2001; Asheim and Isaksen, 2002; Asheim et al., 2011; Archibugi et al., 1999; Evangelista et al., 2002). A number factors and actors play crucial roles in favouring the generation and diffusion of technological knowledge at the local level, including inter-organisation networks, technical agencies and research infrastructures, education and training systems, financial and legal institutions (e.g. intellectual property rights), governance structures, and innovation policies (Iammarino, 2005). This literature emphasizes the importance of universities for many reasons. On the one hand, they are deemed to be crucial to interactive innovation dynamics, contributing the local dynamics of creation, diffusion and adoption of technological knowledge. On the other hand, they are considered to foster regional agglomeration by means of knowledge spillovers from research and educational activities.

In the Triple Helix (TH) approach the core argument is that universities play a key role for innovation processes, especially in increasingly knowledge-based economies (Leydesdorff and Etzkowitz, 1996, 1998; Etkowitz and Leydesdorff, 1997; Etzkowitz and Leydesdorff, 2000). According to the TH model, the *entrepreneurial university* is at the centre of a triadic relationship with industry and government, hence acting pro-actively to generate and diffuse new knowledge (Etzkowitz and Leydesdorff, 2000).[2]

[2] The concept of the entrepreneurial university has been put forward by Etzkowitz (1983), who noted that in that period of increasing costs and static government funds, American universities began to consider the opportunity to source additional funding from patenting the discoveries made by academic scientists, from the sale of results of research carried out under contracts with companies, and from engaging into partnership with businesses.The importance of academic research to industry and to society as a whole has gained novel appreciation since then. Similar trends were taking place in Europe as well, as illustrated by Clark (1998) in his study of five European universities: in fact, among the ingredients of success in each institution he noted an integrated entrepreneurial culture.

In sum, the argument that universities can contribute to the development of local technological trajectories rests upon two key assumptions: firstly, universities increase the production of knowledge by supplying new skilled workforce (university *first mission*) and the results of scientific research (university *second mission*); secondly, the presence of universities leads to the transfer and exchange of knowledge among organisations, notably universities and companies (university *third mission*) (Veugelers and Del Rey, 2014). Academic institutions are assumed to be important sources of localized knowledge spillovers because of their explicit focus on the generation and diffusion of knowledge (Ponds et al., 2010; Audretsch et al., 2005; Del Barrio-Castro and García-Quevedo, 2005; Fritsch and Slavtchev, 2007).[3] According to scholars in this literature, spillovers occur through various channels, including spin-off companies - through which academic knowledge gets commercialised; graduates and researchers moving outside academia; university-industry interactions (Scandura, 2016, 2019) and, importantly, formal as well as informal personal networks of academic and industrial researchers - through which the latest academic knowledge is disseminated (Varga, 2000).

From the previous discussion it follows that knowledge stemming from academic research is likely to play an important role in local innovation processes underling regional technological diversification. In view of these arguments, we can spell out our first hypothesis as follows:

Hp1: Academic inventors positively contribute to the entry of regions into new technological domains.

2.3 Academic inventors and unrelated diversification

While related diversification results from innovations that incrementally build on related technologies, unrelated diversification is expected to stem from breakthroughs that emerge from recombining previously unconnected technologies into a new configuration (Castaldi et al., 2015; Fleming, 2001). This occurs when a region develops new activities that require very different capabilities with respect to existing local activities. Therefore, unrelated diversification tends to be driven by agents who possess special capabilities and a special knowledge set that allow them to successfully combine new and loosely related technological domains. In some cases, such agents built up their capabilities elsewhere: this is the case of migrant workers and migrant entrepreneurs, as well as of multinationals (Colombelli et al., 2016). In some other cases, these agents were specifically supported by

[3] Localised knowledge spillovers are defined as flows of ideas between agents at less than the original cost (Griliches, 1992).

public policies (Dawley et al., 2015; Neffke et al., 2018). Alternatively, unrelated diversification may stem from within the region based on the exploitation of local innovation capabilities that hence represent enabling conditions.

Various scholars work on the topic of unrelated diversification using both case studies (Binz et al., 2016; Dawley et al., 2015) and statistical approaches (see e.g. Boschma and Capone, 2015; Neffke et al., 2018; Colombelli et al., 2016; Montresor and Quatraro, 2017). Within this growing field of enquiry, a number of contributions focus on the enabling conditions for unrelated diversification. Scholars explored the role of national institutions on related versus unrelated diversification. For instance, Boschma and Capone (2015) found that liberal market institutions as compared with coordinated market institutions favour more unrelated diversification at the country level; Cortinovis et al. (2017) did not find any effect of regional formal and informal institutions on the tendency of regions to diversify in related or unrelated activities. Specifically focusing on innovation capabilities, Xiao et al. (2018) showed that knowledge-intensive European regions are more likely to move into unrelated activities, as compared with knowledge-extensive regions in the European periphery, hence showing that innovation capabilities act as substitute for relatedness. Similarly, Montresor and Quatraro (2017) stressed the role of regional specialisation in Key Enabling Technologies (KETs) in engendering regional structural change. In particular, regions with a strong presence of such enabling technologies tend to diversify in unrelated activities (Montresor and Quatraro, 2017).

Insights from the emerging literature on regional unrelated diversification have remained fragmented at best. In particular, while underling that local innovation capacity allows regions to break from their past and to develop new specializations, extant literature is only weakly informative about which innovation capabilities matter. Xiao et al. (2018) rely on the categorization of regions developed by Marsan and Maguire (2011), which is based on innovation as well as socio-demographic and economic variables. While providing a comprehensive assessment of multiple dimensions of regional characteristics, this measure does not allow to disentangle the role of each of them, particularly with respect to the innovation capabilities. Given the increasing importance of science, technology and innovation policies tailored on the needs of localities, it is of key importance to consider the role of individual local enabling conditions for regional diversification.

Comparing advantages and disadvantages of academic and private sector research, Aghion et al. (2008) reason that academic research can be indispensable for early stages of the innovation process. This is because academia allows scientists to freely pursue their own research interests, hence leaving creating control in the hands of scientists. Accordingly, academic research is more likely to result in new research lines, due to the possibility of scientists to wander off in their preferred research directions (Aghion et al., 2008). Moreover, academic institutions play a major role in supporting the creation of networks of learning and recombinations thanks to their well connected international research networks (Boschma and Gianelle, 2014). Therefore, innovations resulting from academic knowledge will be more often breakthroughs that build on the latest knowledge available inside universities and that span the existing technological boundaries, hence allowing regions to diversify in new technological domains.

However, highly complex knowledge such as academic knowledge is hardly transferable outside academia, if not through people. This is primarily due to its characteristics of stickiness and tacitness (Breschi and Lissoni, 2001a, 2003, 2009; Foray, 2004). Such knowledge is in fact highly contextual and difficult to codify, therefore more easily transmitted through face-to-face contacts and personal relationships. As a consequence, mobility of human capital is a crucial mechanism for the local diffusion of knowledge via the mobility of scientists and technologists (Breschi and Lissoni, 2001b). As a matter of fact, previous research shows that the involvement of academic inventors is crucial for firms' innovative performance (see e.g. Allen, 1977; Cockburn and Henderson, 1998; Zucker et al., 2002; Gittelman and Kogut, 2003; Fabrizio, 2009; Cassiman et al., 2018). In particular, when undertaking co-patenting under the umbrella of university-industry joint research activity, academic inventors play an important role in translating tacit and complex early-stage research into valuable technologies (Peeters et al., 2018).

Academic inventors are able to command recombination dynamics across different and loosely related domains, thanks to their peculiar knowledge sets and skills deriving from their distinct educational endowment. This latter has been found to be crucial in teamwork knowledge production, especially as far as inventors trained in science and engineering are concerned (Allen, 1977). In this direction, inventors with higher educational attained, particularly academic inventors, are likely to show better problem solving capacities and the ability to conduct boundary-spanning research, due to their cognitive abilities and attitude towards innovation (March and Simon, 1958; Hambrick and Mason, 1984; Gagné and Glaser, 1987; Walsh, 1995; Pelled, 1996; Hargadon, 2006). Morevoer, recent literature has found that patents spanning technological boundaries are more likely to be introduced by scientist than engineers, supporting the idea that inventors in scientific institutions possess the necessary capabilities to cope with the recombination of knwoledge inputs drom different, and not necessarily related, technological domains (Gruber et al., 2013).

Following such line of reasoning, we postulate that academic inventors contribute to regions' technological diversification because they act as boundary-spanning carriers of university knowledge, hence allowing the generation of innovations that are new and unrelated to existing ones.

Hp2: Academic inventors limit the impact of relatedness on regions' entry into new technological domains

3 Data and methods

3.1 Data sources

We carry out the econometric analysis on a panel dataset of 103 Italian NUTS 3 regions over a ten year period (1998-2008). Our data sources are the Organisation for Economic Cooperation and Development (OECD) RegPat database, the Academic Patenting in Europe (APE-INV)[4] database, along with regional data from Cambridge Econometrics European Regional Database and from the Italian National Institute of Statistics (Istat).

3.2 Variables

3.2.1 Dependent variable

Our dependent variable is the five-year moving average of the yearly count of new technological specialisations in each region, hence measuring the extent of technological diversification inside regions. Following extant literature on the emergence of new economic activities in regional contexts, we define technological specialisations on the basis of the index of Revealed Technological Advantage of region i in technology s at time t (RTA_{ist}) (see e.g. Boschma et al., 2013; Colombelli et al., 2014; Montresor and Quatraro, 2017). Such index is calculated with a Balassa indicator of trade specialisation, redefined in terms of count of patents filed in the corresponding IPC class (Soete, 1987), in each region i at time t.

$$RTA_{ist} = \frac{PAT_{ist}/\sum_{i=1}^{n} PAT_{ist}}{\sum_{s=1}^{m} PAT_{ist}/\sum_{i=1}^{n}\sum_{s=1}^{m} PAT_{ist}}$$

A region is defined as technologically specialised when $RTA_{ist} > 1$ and $0 < RTA_{ist-k} < 1$, that is, when it enters a new specialisation at time t, which did not have at time $t-k$. We hence build a binary indicator called New_RTA_{ist} equalling 1 when region i acquires a new technological specialisation s at time t.

Once identified the cases of regions entering new specialisations, we simply count them across time and space. Given our interest in academic knowledge spillovers at regional

[4]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://archives.esf.org/coordinating-research/research-networking-programmes/social-sciences-soc/current-research-networking-programmes/academic-patenting-in-europe-ape-inv.html`).

level, we based our analysis on a variable aggregated at technology level, $entry_{it}$, which counts the number of new technological specializations of region i at time t, as follows:[5]

$$entry_{it} = \sum_s New\_RTA_{ist}$$

This variable may suffer from the inherent volatility of patent data, because the emergence of a new RTA in a given year may be artificially due to a small number of patent applications in that specific technological domain in the previous year. In order to attenuate this bias, we use the five-year moving average in the construction of the dependent variable (ma_entry_{it}), following previous literature (Montresor and Quatraro, 2017).[6] The five-year moving average of newly acquired specialisations ranges between 0.4 and 87.4, while its mean value is 23.3 (see Table 2).

3.2.2 Independent variables

In this paper we are interested in the effect of spillovers from academic knowledge on regions' technological specialisations. To measure academic knowledge spillovers we use the participation of academic inventors in local patenting activity. As underlined in the literature section, inventive activity is very often a collective activity. Moreover, the formation of researchers' teams involving university scientists is an effective mean to transmit university knowledge to the society, hence generating knowledge spillovers (see e.g. Varga, 2000)

We measure academic inventors' involvement via three variables, which we use separately in the regression analysis and which allow us to test our first hypothesis. These are constructed with data from the APE-INV database. This database allows the identification of academic inventors and their home address within the list of patent applications at the European Patent Office. In the first place, we use a yes/no dummy indicating whether at least one university-based inventor is involved into patenting activity at year t in NUTS 3 region i ($acad\_pat_{it}$). This variable is constructed by tagging patent applications with at least one academic inventor among the list of inventors, and allows to clearly distinguish regions where there are academic inventors from those where there are not. However, it does not capture the extent of inventors' participation into local patenting activity. For this reason, we also work out the decimal count of patents that involve at least one academic inventor at year t in region i ($n\_acadpat_{st}$). With respect to the

[5]For comparison with the extant literature, the estimates carried out at the region-technology level are also reported as a robustness check.

[6]Although arbitrary to a certain extent, a five-year period of time can be reasonably thought long enough to smooth the erratic trend of the flow of patents. Si puo' legare questa spiegazione con la letteratura patent, in cui per esempio le forward citations si prendono sempre a 5 anni?

dummy $acad\_pat_{st}$, this variable provides a measure of the amount of academic knowledge spilling out through patenting in a given region at a given point in time. Finally, we construct a binary indicators for the top quartile of the distribution of the previously described count variable ($top\_acadpat_{it}$). We attach value 1 to all regions where there was the highest count of patents involving university scientists for their inventions (top 25% of $n\_acadpat_{it}$). This dummy identifies regions characterised by a relatively high involvement of academic inventors, thus mirroring high contribution of academic knowledge to local patenting activity. As shown in Table 2, almost half of the yearly observed regions display academic patenting (mean of $acad\_pat_{it} = 0.48$); the mean count of patents involving academic scientists per region per year is 1.12 in the full sample, while it is 2.31 in the sample of regions where there is some academic patenting activity (that is, where $acad\_pat = 1$); finally, 23% of regions display intense involvement of university scientists (mean of $top\_acadpat = 0.23$).

To test the second hypothesis of this work we interact a given measure of academic inventors' participation to local patenting activity with an index of relatedness. Relatedness measures the extent of regions' reliance on related technological domains, since it measures the proximity of newly acquired specialisations, as measured by $entry_{it}$, to pre-existing ones. Following extant research (see e.g. Montresor and Quatraro, 2017), we rely on the relatedness index proposed by Hidalgo et al. (2007), who measure proximity between product pairs at country level. We adapted their measure to our framework by looking at the technology pairs at region level. We exploit patent technological classes to proxy for technologies. Firstly, we measure proximity between a given new technology s at time t and the technologies in which the region was specialised at time $t-k$. Proximity is defined as the minimum of the pairwise conditional probability of a region having RTA in a technology s, given that it has RTA in another technology z:

$$prox_{s,z,t} = \min\{P(RTA_{s,t}|RTA_{z,t}), P(RTA_{z,t}|RTA_{s,t})\}$$

Secondly, all of the proximity linkages found for each technology in which the region was specialised at time $t-k$ are grouped together through a density index (one for each technology), as follows:

$$dens_{izt-1} = \frac{\sum_{s\neq z} prox_{szt-1} New\_RTA_{ist}}{\sum_{s\neq z} prox_{szt-1}}$$

An average density is then calculated with respect to all new technologies in region i:

$$relatedness_{it} = \sum_{s\neq z} dens_{izt-1} \times \frac{New\_RTA_{izt}}{\sum_{z\neq s} New\_RTA_{izt}}$$

Such average density is a proxy for the extent to which the new technological advantages (RTA) that a region gains at time t are, on average, close to those in which it had gained an advantage previously (at $t-k$). In other words, it is a proxy for relatedness. Similarly to the dependent variable, we work out the five year moving average of relatedness ($ma\_relatedness_{it}$) in order to tackle the intrinsic volatility of patent applications.

3.2.3 Control variables

We construct a vector of control variables to better isolate the role of academic inventors as carriers of knowledge spillovers for regional diversification patterns. In the first place, we control for other channels throughout which universities contribute to the local economy. As pointed out in the literature section, besides fostering knowledge transfer and exchange, academic institutions contribute to the local production of knowledge by supplying skilled human capital to the labour market along with the results of scientific research (Veugelers and Del Rey, 2014). In order to account comprehensively for the role of universities in the local economy, we hence control for the percentage of science and technology graduates (ST_grad_{it}) per thousand inhabitants aged 20-29, and for the level of R&D expenditure of universities ($R\&D\_univ_{it}$). Both variables are constructed using data from ISTAT.

Secondly, we control for new firm formation to account for a potentially important source of technological diversification, namely new firms entering the local economy. To measure firm formation we work out the share of new firms at time t over registered firms at $t-1$ (new_firms_{it}), using data gathered from the Union of the Chambers of Commerce (Unioncamere) through the Movimprese dataset. These statistics exclude those types of entrepreneurial activities that are not subject to compulsory registration with the Chamber of Commerce.[7] Finally, we include region-level gross domestic product and employment, to account for local level determinants related to the size and economic performance of localities. Data for these variables are collected from Cambridge Econometrics European Regional Statistics. All variables are listed and their sources are reported in Table 1, while their descriptive statistics and correlation matrix are presented in Tables 2 and 3, respectively.

Given the skewness of some of the continuous variables, we transform them so to smooth their trend. We apply the inverse hyperbolic sine transformation that allows not to lose any zero in the variables.[8] For consistency and to ease interpretation of the results, we

[7]We may also include the region total R&D expenditure as a driver of diversification, but this information is not fully and systematically available at NUTS3 level. In addition, the total R&D expenditure is expected to be partly captured by (and highly correlated to) university R&D as well as by the last set of control variables, namely gdp and employment.

[8]This is an alternative to the Box-Cox transformations, defined by the following formula: *inverse*

transform all continuous variables using the same method.

TABLES 1, 2, 3 ABOUT HERE

3.3 Methodology

To test our hypotheses we estimate the following equations:

$$ma\_entry_{i,t} = \beta_0 + \beta_1 acad\_involv_{i,t} + \beta_2 ma\_relatedness_{i,t} + \gamma X_{i,t} + \epsilon \quad (1)$$

$$\begin{aligned} ma\_entry_{i,t} = \beta_0 + \beta_1 acad\_involv_{i,t} + \beta_2 ma\_relatedness_{i,t} \\ + \beta_3 acadinvol * related_{i,t} + \gamma X_{i,t} + \epsilon \end{aligned} \quad (2)$$

Where $acad\_involv_{i,t}$ indicates the use of one of the three variables that measure academic inventors' involvement into local patenting activity ($acad\_pat_{it}$, $n\_acadpat_{it}$, $top\_acadpat_{it}$), and X_{it} is the vector of control variables.

We employ various panel data regression techniques. Specifically, we estimate a fixed effects model followed by a mixed effects model and a spatial regression model. The fixed effects model is the first preferred method because of the NUTS 3 region-level unobservable factors that can not be measured. A mixed-effects model is used to account for the hierarchical structure of our data, which is due to the administrative structure of Italian regions. In fact, 103 NUTS 3 regions are nested within a higher-level structure, this being made up of 21 NUTS 2 regions (19 regions and 2 autonomous provinces). To account for NUTS2 as well as NUTS3 variation, we estimate a multi-level mixed effects panel model. A multi-level, sometimes also called a hierarchical, random coefficient or mixed-effect model, is defined as a model that relates a dependent variable to predictor variables at more than one level (Luke, 2004). Finally, we implement a spatial regression model to measure the effect of academic knowledge spillovers when their spatial lags are accounted for. In particular, we use the spatial Durbin auto-regressive model where we control for the spatially lagged independent variables measuring academic inventors' involvement in local patenting activity.

Additionally, we implement two sets of regressions to check the robustness of our results. First, we replicate the fixed and mixed effects panel regressions to estimate equations (1) and (2), but we employ a different measure of academic inventors' involvement into local patenting activity. To account for the precise amount of university-based scientists in

$y = log[y_i + (y_i^2 + 1)^{1/2}]$. 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 and Magee, 1990).

patenting, we work out the share of academic inventors per each patent. We sum up the shares so calculated at region-year level so to end up with the exact fractional count of academic inventors per region-year ($acad\_inv_{it}$). Secondly, we implement a population-averaged probit model at the technology-region level that allows comparability with the usual regression framework in the economic geography literature on regional technological specialisations, where the analysis is carried out at technology-region level (see e.g. Boschma et al., 2014, 2013; Colombelli et al., 2014). In so doing, we estimate the determinants of the entry into new regional technological specialisations, where the latter is measured by a dichotomous indicator equalling 1 each time regions enter a new specialisations ($entry_{it}$).

4 Academic inventors and recombinant capabilities: descriptive evidence

In this work, we argue that university-based inventors contribute to the technological diversification of the regions where they are located because they are able to successfully manage the recombination process, not just among similar and related technological domains, but also across different and not necessarily related domains (see e.g. Gruber et al., 2013). Hence, we postulate that academic knowledge spillovers transmitted by individual scientists are conducive of unrelated specialisation within regions. Academic scientists are endowed with a special set of knowledge and skills that allow them to successfully engage in the recombinatorial activity that is necessary to produce new knowledge and innovation (Gagné and Glaser, 1987; Hargadon, 2006). As a matter of fact, it has been shown that academics' involvement in industrial inventive activity lead to patents that have stronger scientific links (higher citations to non-patent literauture), higher complexity (larger technological patent scope), higher technological impact and higher probability of being novel, with respect to non-academic patents (Ljungberg and McKelvey, 2012; Lerner, 1994; Callaert et al., 2006).

In order to empirically support the superior recombinant capabilities of academic inventors, we provide descriptive evidence about the difference between patents generated by inventor teams involving academic scientists and patents not involving any university-based inventor. Table 4 shows the figures for a set of OECD quality indicators (Squicciarini et al., 2013), for the whole sample of Italian patents in years 1998-2008 as well as for the sub-samples of academic and non-academic ones.[9] We perform t-tests to assess the

[9]We used nearly all the indicators provided by the OECD. We excluded those available for few observations only, with the exception of *generality*, which we kept because both samples have the same percentage of non-missing values (37%).

significance of the difference in means across the two sub-samples.

Patents involving academic inventors display, on average, larger means than those not generated by academics, in all indicators but two, namely the count of forward citations received in a 5 and 7 year time window (*fwd_ cits5* and *fwd_ cits7*). Yet, the count of the most important forward citations (*fwd_ cits5_ xy* and *fwd_ cits7_ xy*) are significantly higher, thus showing the higher technological impacts of patents involving academic scientists. In addition, patents invented by mixed teams of inventors display a significantly lower mean count of backward citations (*bwd_ cits*). This is in line with our argument as it shows that those inventions rely less on extant patents, hence arguably less on pre-existing knowledge stocks. In fact, large numbers of backward citations may signal the innovation to be more incremental in nature (Lanjouw and Schankerman, 2001). Relatedly, we also find that these patents rely more on non-patent literature (*npl_ cits*), supporting the hypothesis that academic inventors have stronger scientific links.

All other indicators show that patents invented by teams involving academic scientists have higher complexity (larger *patent_ scope* and *claims*), higher relevance for subsequent inventions (higher *generality*), higher breadth of the technology fields on which patents rely (larger *originality*),[10] and higher novelty with respect to the predecessors they rely upon (higher *radicalness*).

The descriptive evidence here presented is in line with extant research (see e.g. Ljungberg and McKelvey, 2012; Lerner, 1994; Callaert et al., 2006) and strengthens the arguments that we bring forward in this work. In particular, it provides substantial support to the argument that patents generated by teams involving academic inventors may represent boundary spanning inventions through which regions enter into new and less related technological domains.

TABLE 4 ABOUT HERE

5 Results

5.1 Main results

Table 5 displays the results of the fixed effects estimation of equations (1) and (2). Relatedness to pre-existing specialisations significantly explains the extent of regions' entry into new technological domains, as can be noted from the positive and significant coefficients

[10]The patent originality measure was first proposed by Trajtenberg et al. (1997), who operationalise the concept of knowledge diversification and its importance for innovation: inventions relying on a large number of diverse knowledge sources are supposed to lead to original results (i.e. on patents belonging to a wide array of technology fields) (Squicciarini et al., 2013).

of $ma\_relatedness_{it}$ across all estimates. This result is expected and fully in line with extant research.

Let us now turn to the hypothesised positive contribution of academic inventors to regional diversification and their moderating role on relatedness. Our arguments are supported by columns (3), (5) and (7), where both hypotheses are tested. Regions displaying academic knowledge spillovers vehiculated by university inventors show a higher count of new specialisations. In particular, regions where academic inventors are involved ($acad\_pat_{it} = 1$) have a 5% higher count of new specialisations with respect to regions where there is no involvement of university scientists. Similarly, a 1% increase in the count of patents involving academic inventors ($n\_acadpat_{it}$) generates a 5% increase in the new specialisations. Finally, the highest involvement of academic scientists ($top\_acadpat_{it} = 1$) is associated to a 6.7% higher count of new specialisations.

The significantly negative interaction terms between academic knowledge spillovers and relatedness show that university scientists moderate the role of relatedness, particularly when the precise amount of patents involving academics is used (coefficient of $n\_acadpat_{it} * ma\_relatedness_{it}$ significant at 1% level). Therefore, university based scientists reduce the tight reliance of regions upon pre-existing technological domains. Figures 1, 2 and 3 show the interaction effects. It can be noted that the slope of the relatedness effect is lower when academic inventors are involved, with respect to the case of no involvement, thus mirroring a smaller effect of relatedness on the dependent variable (Figure 1). A similar pattern is traced when the dummy indicator $top\_acadpat_{it}$ is interacted with relatedness (Figure 3). Figure 2 shows that the larger the count of patents involving academic inventors, the smaller the effect of proximity to existing specialisations on the extent of regions' entry into new technological areas.

As for the control variables, university graduates in science and technology are found to positively influence the entry of regions into new specialisations. on the contrary, the coefficient of new firms' formation is only weakly significant, and just in a few regressions. The results of the mixed effects regressions, presented in Table 6, are in line with what has just been discussed. In particular, a 8% larger amount of new specialisations is associated to regions where academic inventors participate to local patenting activities, as well as to a 1% increase in patents involving them; similarly, a +10% in specialisations is linked to regions where the largest amount of university scientists take part to local patenting dynamics.

TABLES 5, 6 ABOUT HERE

FIGURES 1, 2, 3 ABOUT HERE

5.2 Robustness checks

The first set of regressions carried out in order to check the robustness of the main results is presented in Table 7. The coefficients of $acad\_inv_{it}$, measuring the fractional count of academic inventors per region-year, is positive and significant across all estimations. Therefore, the larger the amount of university-based scientists involved in local patenting activity, the higher the amount of new specialisations entered by regions. In addition, the interaction term between $acad\_inv_{it}$ and relatedness is negative and significant in every model, hence allowing once again not to reject the hypothesis about the moderating role of university knowledge spillovers. Therefore, whether we measure the importance of university knowledge spillovers by considering inventions (as in the main estimates) or inventors (as in the robustness checks), we obtain comparable results that sustain our hypotheses.

The second set of regressions is meant to control for possible spatial dependence in our data. Following Montresor and Quatraro (2017), geographical spillovers might be at stake when investigating regional technological diversification. The spatial regressions in Table 8 also provide support to our findings (see columns 1, 5 and 9), although the magnitude of the effects is larger than those of the previous estimates. As for the coefficients of the spatially lagged variables, we find that spatial dynamics seems to be at stake to some extent only as far as $ma\_entry_{i,t}$ is concened, while academic involment is significant only in one out of three estimations.

Since exclusive reference to coefficients may not be reliable in ascertaining the existence of spatial spillovers (LeSage and Pace, 2009) , following Elhorst (2014) in the other columns of Table 8 we look at the effects that a change in our explanatory variables in a particular region has on the dependent variable in both that region (direct effect) and on closer regions (indirect effect), as well as on their sum (total effect).

Interestingly, these results show no significant spatial effects of academic inventors' participation to patenting activity, since the spatial lags of academic involvement is never significant. This result is in line with the well-known argument that knowledge spillovers are most often spatially bounded (see e.g. Breschi and Lissoni, 2001a).

The last set of regressions allows to test the sensitivity of our results by comparing them to the most common regression framework in the economic geography literature on regional technological specialisations, where the analysis is carried out at technology-region level (see e.g. Boschma et al., 2014, 2013; Colombelli et al., 2014). In line with our previous estimations, Table 9 shows that the probability of a region to enter a new technological specialisation is positively associated with relatedness as well as with academic knowledge spillovers. In addition, the coefficients of the interaction term provide grounds to the argument that academic inventors lessen the role of proximity to pre-existing specialisations. Our arguments are therefore robust also when implementing a technology-region level framework.

TABLES 7, 8, 9 ABOUT HERE

6 Discussion and conclusion

This work has investigated the relationship between university knowledge - transmitted by academic inventors - and regional technological specialisations, motivated by the increasing academic and policy interest in the determinants of sustainable regional technological trajectories (see e.g. Boschma et al., 2017; Boschma, 2017). We have shown that the involvement of academic inventors into local patenting dynamics is positively related to the amount of new technological specialisations entered by a region. This result is robust to the employment of several measures of academic inventors' involvement, including the count of patents invented by mixed teams of academic and non-academic inventors and the exact count of university inventors inside regions. Crucially, we also show that academic inventors mitigate the reliance of localities upon pre-existing specialisations. Specifically, we find that the role of technological relatedness for regional specialisation is smaller in regions where university scientists are involved in patenting, with respect to regions where these are not (or less) involved. The empirical analysis relies upon panel data regression techniques implemented on a panel of Italian NUTS 3 regions with data available over years 1998-2009.

Our results offer new insights on the factors influencing regional diversification strategies, hence contributing to the flourishing stream of economic geography literature investigating such issues. In particular, the results of this work contribute to the academic debate around related and unrelated technological diversification of a territory (see e.g. Frenken et al., 2007; Boschma and Capone, 2015; Cortinovis et al., 2017). While extant research shows that regions tends to diversify into technologically related economic activities, recent studies contends that enduring economic growth is likely to be generated by unrelated diversification. Yet, the empirical evidence on the driving factors of unrelated diversification is still scant and, as a consequence, not conclusive. Our work brings an important novelty within this framework, underscoring the key role of local innovation capacity (Xiao et al., 2018), focusing specifically on the role of local academic institutions and academic inventors. With this regard, we share the view of Tanner (2014), whose study contends that the process of regional diversification relies also on knowledge generated by non-industrial actors such as universities and research institutes. The author claims that the role of universities and research centres in the process of regional diversification should not be neglected, as it has been done so far in the literature (Tanner, 2014). Similarly, Boschma (2017) underlines that a micro-perspective on regional diversification should not be limited to purely economic actors, since public agencies, including universities, can play a major role in developing new industries unrelated to the existing development paths. We took on board these suggestions with the aim of exploring the proposed research venues about the role of academic institutions for regional diversification. Our work hence tries to bridge the economic geography literature on regional specialisation with the economics of innovation literature studying the role of academic institutions for economic development. To the best of the authors' knowledge, this is the first attempt to do so.

We show that academic knowledge has a pivotal role for unrelated diversification, since it allows the entry of regions into a larger number of new, unexplored and only loosely related technological domains. Our argument rests on the assumption that knowledge spillovers transmitted by academic scientists involved into local patenting activity lead to inventions that spans the existing technological boundaries. In fact, by comparing patents involving academic scientists with the rest of the inventions on a number of key characteristics, we show that inventions generated by teams involving academic and non-academic scientists tend to be less related to the existing stock of technological knowledge; that is to say, they are technologically unrelated to previous domains. In our regression analysis, regions that feature higher involvement of academic inventors, as well as higher count of patents generated by mixed teams of inventors, display a larger count of new technologically unrelated specialisations with respect to other regions. This provides support to the hypothesised positive influence of academic inventors on regional diversification.

Secondly, this study provides substantial empirical evidence on the substitution effect between technological relatedness and academic inventors. This result goes in the direction outlined by Boschma (2017), who argue that there is a need to increase the understanding of the conditioning factors facilitating more related or more unrelated diversification in regions (Boschma and Capone, 2015; Montresor and Quatraro, 2017). The argument that we bring forward, confirmed by the data, is that relatedness to pre-existing technological domains is less relevant for the amount of new specialisations entered by a region, when university scientists are involved in patenting activities. This happens because academic scientists, who are endowed with a special set of skills and expertise that allow them to cope with knowledge recombination across unrelated technological domains (Gruber et al., 2013), are less reliant on the existing stocks of knowledge. Besides a direct role of academic inventors for the entry of regions into new technological domains, we hence document an indirect effect of scientists' involvement into local patenting dynamics: by generating inventions that span across technological boundaries and by contributing to their diffusion outside academia, academic inventors limit the reliance of a territory upon related technologies, thus representing a conditioning factor facilitating unrelated diversification. Such indirect effect is highly important as it helps avoiding potential lock-in effects deriving from related diversification (Saviotti and Frenken, 2008). Negative sector-wide performances may in fact be dangerous particularly in regions pursuing diversification strategies based on related diversification. Therefore, long-term sustainable development trajectories should rely less on related diversification in order to ensure economic growth together with decreasing unemployment (Frenken et al., 2007; Davies and Tonts, 2010; Neffke et al., 2018).

As with any study, this work has a few caveats, including the well-known limitations in the use of patent statistics as indicators of technological activity and the measure of academic knowledge spillovers by means of academic inventors' participation into local patenting activity. With respect to the first issue, prior research proves that patent data represent a reliable measure of innovation (Acs and Audretsch, 1989; Archibugi and Planta, 1996); in addition, patents are particularly useful in the context of regional innovation patterns (see e.g. Acs et al., 2002). As for the measure of knowledge spillovers, we exploit information on academic inventors to create a reliable indicator of knowledge flowing outside academia on the ground of the well-known consideration that knowledge diffuses primarily through people (Breschi and Lissoni, 2001b). This is particularly true for highly complex knowledge, such as academic knowledge, characterised by being sticky and tacit (see e.g. Breschi and Lissoni, 2001a; Foray, 2004). Extant research also shows that academic inventors have a key role for companies' as well as regions' innovation perfomance (Meyer et al., 2003; Lissoni, 2010). Yet, in the empirical analysis we add two measures of other relevant channels through which academic knowledge diffuses in the society - the percentage of science and technology graduates and the level of R&D expenditure of universities - (Veugelers and Del Rey, 2014), with the aim of properly isolating the influence of academic inventors on regional diversification.

Nonetheless its limitations, this study offers interesting insights both for the academic literature and for the policy discourse around regional specialisation, and more generally, regional development. As underlined in the previous paragraphs of this section, this study contributes to the literature by empirically showing that academic knowledge has a major role in regional diversification trajectories and that it also acts as a moderating factor of technological relatedness. Importantly, we highlight that academic scientists have a key role in the knowledge dynamics behind unrelated diversification, as they allow the generation of knowledge that spans across technological boundaries. Therefore, we believe that this work sheds new light on the process of regional technological diversification and, hopefully, paves the way for future research aimed at uncovering other key determinants of successful and sustainable technological development.

From the policy standpoint, the findings of this work contribute to the long-lasting debate on local development strategies by offering new hints on the factors upon which regions should leverage in order to activate sustainable development trajectories. While the regional diversification thesis offers new possibilities to policy makers to be more strategic in designing regional innovation policies (Tanner, 2014), our study underscores that it is of key importance to include non-economic actors like universities in order to successfully promote the development of new emerging industries. Academic institutions have a major role in the generation of new knowledge and, consequently, in technological development. Therefore, supporting the interaction between those who are primarily involved in the knowledge generation process inside universities, such as researchers and scientists, and the society, is of paramount importance. In particular, our findings highlight that the interaction between academic scientists and inventors inside companies is beneficial to the generation of inventions that opens up new and unrelated technological trajectories. Policy measures supporting academia-business interactions specifically aimed at the generation of new research discoveries and, eventually, their protection through patenting, are likely to help achieve regional unrelated diversification. Such measures will also allow to overcome the different and often diverging priorities of the university research system and companies (see e.g. Aghion et al., 2008; Dasgupta and David, 1994): on the one hand, research activity aimed at the creation of new knowledge certainly represents an incentive for academic scientists, who are often highly interested in conducting pure research; on the other hand, patent protection may incentivize companies to engage in that type of research, as it allows them to appropriate the economic benefits of their inventions. By doing so, patents create the basis for emerging industries because they secure the exploitation of inventions for the years to come.

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7 Tables

Table 1: Variable list and description

		Variables	Description	Data source
Dep. var.	1	ma_entry	5y moving average of the count of new technological specialisations	OECD RegPat
Indep. var.	2	ma_relatedness	5y moving average of proximity between new and pre-existing technological specialisations	OECD RegPat
	3	acad_pat	0/1 dummy for at least one academic inventor in patent	APE-INV
	4	n_acadpat	Count of patents with at least one academic inventor in patent	APE-INV
	5	top_acadpat	0/1 dummy for top 25% of n_acadpat	APE-INV
Contr. var.	6	share_new_firms	New registered firms at time t / registered firms at t-1	??
	7	S&Tgrad	Science and technology graduates per 000s inhabitants aged 20-29 (%)	Istat
	8	R&Duniv	R&D expenditure of universities	Istat
	9	gdp	Gross domestic product (000s euros)	Cambr. Econom. ERD
	10	empl	Employment (000s)	Cambr. Econom. ERD

Table 2: Descriptive statistics

Variable	**Obs**	**Mean**	**Std Dev**	**Min**	**Max**
ma_entry	1,030	23.37961	18.58636	0.4	87.4
ma_relatedness	1,030	0.012044	0.015082	2.86E-05	0.086413
acad_pat	1,030	0.485437	0.500031	0	1
n_acadpat	1,030	1.121391	2.761948	0	29.75
top_acadpat	1,030	0.238835	0.426579	0	1
share_new_firms	1,030	0.069071	0.00933	0.036698	0.109761
S&Tgrad	1,030	8.526005	4.276594	0.075171	18.0087
R&Duniv	1,030	48482.72	64217.69	0	595992.4
gdp	1,030	13.76505	19.21432	1.646	148.935
empl	1,030	234.5869	297.1919	31.909	2164.37

Table 3: Correlation matrix

		1	2	3	4	5	6	7	8	9	10
1	ma_entry	1									
2	ma_relatedness	0.9550*	1								
3	acad_pat	0.4793*	0.4139*	1							
4	n_acadpat	0.5460*	0.6396*	0.4182*	1						
5	top_acadpat	0.4709*	0.4493*	0.5767*	0.6202*	1					
6	share_new_firms	0.1283*	0.1223*	0.1240*	0.0867*	0.0902*	1				
7	S&Tgrad	0.4742*	0.4638*	0.3394*	0.5591*	0.4532*	-0.0566	1			
8	R&Duniv	0.5260*	0.5653*	0.3525*	0.7269*	0.4803*	0.0752*	0.7366*	1		
9	gdp	0.6482*	0.7321*	0.3344*	0.8273*	0.4388*	0.0868*	0.6454*	0.9028*	1	
10	empl	0.6408*	0.7174*	0.3504*	0.8130*	0.4563*	0.0811*	0.6660*	0.9258*	0.9942*	1

* p<0.1

Table 4: OECD Quality Indicators: mean comparison test

	Full sample N=50831		Academic N=2490		Non-academic N=48341		T-test	
	obs	mean	obs	mean	obs	mean	diff in mean	signif
patent_scope	50827	1.658134	2490	2.127711	48337	1.633945	0.493766	***
family_size	50831	5.302119	2490	6.295582	48341	5.250946	1.044636	***
bwd_cits	50831	5.016624	2490	3.918876	48341	5.073168	-1.154292	***
npl_cits	50831	1.196022	2490	3.828112	48341	1.060446	2.767666	***
claims	50831	13.42616	2490	16.24096	48341	13.28117	2.95979	***
claims_bwd	48663	3.800767	2291	6.463937	46372	3.669193	2.794744	***
fwd_cits5	50831	0.861207	2490	0.798795	48341	0.864422	-0.0656263	
fwd_cits5_xy	50831	0.367138	2490	0.395582	48341	0.365673	0.0299093	**
fwd_cits7	50831	1.144853	2490	1.173494	48341	1.143377	0.030117	
fwd_cits7_xy	50831	0.480534	2490	0.530121	48341	0.477979	0.0521411	**
generality	18384	0.303785	920	0.418433	17464	0.297746	0.1206867	***
originality	49575	0.641131	2294	0.70887	47281	0.637845	0.0710254	***
radicalness	49588	0.300473	2295	0.352633	47293	0.297942	0.0546914	***

*** p<0.01, ** p<0.05

Table 5: Regression results - Fixed effects regressions (1 year lagged regressors)

DV: ma_entry **MODEL: fixed effects**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
ma_relatedness		5.795***	7.470***	5.746***	8.452***	5.801***	7.109***
		(1.322)	(1.608)	(1.325)	(1.616)	(1.322)	(1.480)
acad_pat		0.0245	0.0498**				
		(0.0165)	(0.0215)				
acad_pat*ma_relatedness			-2.251*				
			(1.234)				
n_acadpat				0.0166	0.0520***		
				(0.0146)	(0.0190)		
n_acadpat*ma_relatedness					-2.060***		
					(0.710)		
top_acadpat						0.0254	0.0671**
						(0.0207)	(0.0297)
top_acadpat*ma_relatedness							-2.690*
							(1.374)
share_newfirms	-1.866*	-1.856*	-1.754	-1.908*	-1.886*	-1.952*	-1.997*
	(1.111)	(1.099)	(1.099)	(1.100)	(1.095)	(1.101)	(1.099)
S&Tgrad	0.126**	0.113**	0.111**	0.108**	0.108**	0.109**	0.111**
	(0.0525)	(0.0520)	(0.0520)	(0.0522)	(0.0520)	(0.0522)	(0.0521)
R&Duniv	-0.00424	-0.00470	-0.00506	-0.00463	-0.00493	-0.00463	-0.00465
	(0.00805)	(0.00797)	(0.00796)	(0.00797)	(0.00794)	(0.00797)	(0.00796)
gdp	-0.263	-0.258	-0.244	-0.268	-0.289	-0.267	-0.256
	(0.272)	(0.269)	(0.269)	(0.269)	(0.268)	(0.269)	(0.269)
empl	-0.145	-0.163	-0.176	-0.145	-0.138	-0.146	-0.158
	(0.267)	(0.264)	(0.264)	(0.264)	(0.263)	(0.264)	(0.264)
Constant	4.918***	4.945***	4.966***	4.878***	4.879***	4.885***	4.911***
	(1.157)	(1.145)	(1.143)	(1.146)	(1.142)	(1.146)	(1.144)
Observations	1,030	1,030	1,030	1,030	1,030	1,030	1,030
Number of NUTS3	103	103	103	103	103	103	103
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.276	0.293	0.296	0.292	0.299	0.293	0.295
F	24.87	23.60	22.47	23.52	22.82	23.54	22.45
Adj-R2	0.184	0.202	0.204	0.201	0.207	0.201	0.203
p	0	0	0	0	0	0	0
log likelihood	385.1	397.3	399.1	396.7	401.5	396.9	399.0

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

Table 6: Regression results - Mixed effects regressions (1 year lagged regressors)

DV: ma_entry **MODEL: mixed effects**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
ma_relatedness		12.80***	16.49***	12.60***	19.50***	12.55***	16.46***
		(2.586)	(2.823)	(2.615)	(2.911)	(2.611)	(2.829)
acad_pat		0.0339**	0.0826***				
		(0.0165)	(0.0219)				
acad_pat*ma_relatedness			-4.541***				
			(1.366)				
n_acadpat				0.0124	0.0855***		
				(0.0145)	(0.0197)		
n_acadpat*ma_relatedness					-4.389***		
					(0.800)		
top_acadpat						0.0198	0.102***
						(0.0207)	(0.0305)
top_acadpat*ma_relatedness							-5.653***
							(1.551)
share_newfirms	-1.564	-1.862*	-1.697	-1.914*	-1.997*	-1.943*	-2.120*
	(1.101)	(1.086)	(1.083)	(1.087)	(1.081)	(1.088)	(1.086)
S&Tgrad	0.120**	0.100**	0.0970*	0.0977*	0.0916*	0.0980*	0.100**
	(0.0513)	(0.0507)	(0.0505)	(0.0509)	(0.0506)	(0.0509)	(0.0507)
R&Duniv	-0.00619	-0.00665	-0.00744	-0.00653	-0.00750	-0.00653	-0.00675
	(0.00813)	(0.00798)	(0.00797)	(0.00799)	(0.00798)	(0.00799)	(0.00797)
gdp	0.415*	0.306	0.341	0.299	0.368	0.302	0.356
	(0.238)	(0.236)	(0.235)	(0.237)	(0.234)	(0.236)	(0.236)
empl	0.231	0.171	0.137	0.184	0.126	0.185	0.122
	(0.242)	(0.239)	(0.238)	(0.240)	(0.237)	(0.240)	(0.239)
Constant	0.726	1.297*	1.368*	1.258*	1.360*	1.248*	1.438*
	(0.751)	(0.748)	(0.743)	(0.750)	(0.736)	(0.750)	(0.746)
Observations	1,030	1,030	1,030	1,030	1,030	1,030	1,030
Number of groups	21	21	21	21	21	21	21
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
chi2	593.5	606.4	636.4	596.9	694.7	598.6	634.9
p	0	0	0	0	0	0	0
log likelihood	77.50	89.85	96.50	87.98	102.2	88.42	96.25

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

Table 7: Robustness check - Fixed effects and mixed effects regressions (1 year lagged regressors)

DV: ma_entry	**Fixed effects**		**Mixed effects**	
	1	**2**	**3**	**4**
ma_relatedness	5.563***	10.40***	12.11***	23.32***
	(1.325)	(1.728)	(2.606)	(3.008)
acad_inv	0.0233**	0.0533***	0.0229**	0.0796***
	(0.0101)	(0.0122)	(0.0101)	(0.0126)
acad_inv*ma_relatedness		-2.284***		-4.421***
		(0.531)		(0.605)
share_newfirms	-1.891*	-1.816*	-1.895*	-1.899*
	(1.097)	(1.087)	(1.085)	(1.068)
S&Tgrad	0.0988*	0.101*	0.0874*	0.0854*
	(0.0523)	(0.0518)	(0.0510)	(0.0502)
R&Duniv	-0.00491	-0.00577	-0.00681	-0.00890
	(0.00795)	(0.00788)	(0.00797)	(0.00790)
gdp	-0.264	-0.295	0.302	0.378
	(0.268)	(0.266)	(0.236)	(0.231)
empl	-0.160	-0.162	0.178	0.115
	(0.263)	(0.261)	(0.239)	(0.234)
Constant	4.952***	5.014***	1.283*	1.376*
	(1.143)	(1.132)	(0.748)	(0.726)
Observations	1,030	1,030	1,030	1,030
Adj-R2	0.204	0.219		
Number of code_province	103	103		
Number of groups			21	21
Year FE	Yes	Yes	Yes	Yes
F	23.88	23.99		
ll	399.0	409.4	89.83	114.4
chi2			605.8	757.6
p	0	0	0	0

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

Table 8: Regression results - Spatial Durbin regressions (1 year lagged regressors)

DV: ma_entry Model: Spatial Durbin	1 Main	2 Direct effects	3 Indirect effects	4 Total effects	5 Main	6 Direct effects	7 Indirect effects	8 Total effects	9 Main	10 Direct effects	11 Indirect effects	12 Total effects
ma_relatedness	38.89***	39.38***	27.01	66.39	29.91***	30.50***	40.00	70.50	27.00***	27.42***	19.31	46.72
	(7.617)	(7.852)	(87.18)	(88.33)	(6.256)	(6.565)	(148.4)	(149.9)	(7.083)	(7.357)	(63.83)	(65.65)
acad_pat	0.592***	0.603***	1.878	2.481								
	(0.0870)	(0.0883)	(3.061)	(3.091)								
ma_relatedness*acad_pat	-37.08***	-37.02***	-25.04	-62.06								
	(7.652)	(7.686)	(73.98)	(74.97)								
n_acadpat					0.264***	0.265***	0.377	0.642				
					(0.0512)	(0.0510)	(1.154)	(1.167)				
ma_relatedness*n_acadpat					-13.57***	-13.65***	-18.69	-32.34				
					(1.676)	(1.847)	(80.64)	(81.46)				
top_acadpat									0.570***	0.581***	1.878	2.458
									(0.116)	(0.119)	(3.312)	(3.356)
ma_relatedness*top_acadpat									-32.48***	-32.38***	-22.32	-54.70
									(6.537)	(6.619)	(91.72)	(93.26)
S&Tgrad	0.0235	0.0231	-0.000398	0.0227	0.0854	0.0860	0.120	0.206	0.0727	0.0717	0.0395	0.111
	(0.0739)	(0.0715)	(0.232)	(0.261)	(0.0735)	(0.0720)	(0.702)	(0.721)	(0.0770)	(0.0739)	(0.306)	(0.329)
R&Duniv	0.0461*	0.0460**	0.0307	0.0767	0.0713**	0.0723**	0.0988	0.171	0.0693**	0.0696**	0.0445	0.114
	(0.0240)	(0.0229)	(0.105)	(0.110)	(0.0321)	(0.0312)	(0.472)	(0.479)	(0.0302)	(0.0291)	(0.229)	(0.235)
New firms	-0.592***	-0.582***	-0.403	-0.985	-0.535***	-0.530**	-0.746	-1.276	-0.580***	-0.570***	-0.370	-0.940
	(0.201)	(0.203)	(1.539)	(1.579)	(0.207)	(0.211)	(3.815)	(3.873)	(0.216)	(0.217)	(2.050)	(2.096)
gdp	2.994***	2.991***	1.956	4.948	3.092***	3.113***	4.083	7.196	3.108***	3.107***	2.054	5.162
	(0.485)	(0.464)	(5.736)	(5.752)	(0.526)	(0.526)	(17.20)	(17.35)	(0.546)	(0.535)	(8.587)	(8.687)
empl	-1.907***	-1.920***	-1.201	-3.120	-2.053***	-2.080***	-2.621	-4.701	-2.016***	-2.031***	-1.340	-3.371
	(0.504)	(0.475)	(2.978)	(3.005)	(0.550)	(0.528)	(9.799)	(9.892)	(0.567)	(0.541)	(4.785)	(4.880)
rho	0.305				0.457**				0.372*			
	(0.198)				(0.186)				(0.209)			
sigma2_e	0.184***				0.179***				0.195***			
	(0.0180)				(0.0188)				(0.0194)			
Wx academic involvement	0.891**				0.0316				0.888			
	(0.420)				(0.341)				(0.683)			
Observations	1,030				1,030				1,030			
R-squared	0.810				0.816				0.798			
Number of NUTS3	103				103				103			
Year FE	Yes				Yes				Yes			
ll	-591.3				-576.3				-620.4			

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

Table 9: Robustness check - Probit regressions at technology-region level (1 year lagged regressors)

DV: entry (0/1) **MODEL: probit**	**1**	**2**	**3**	**4**
relatedness	0.628***	0.634***	0.423***	0.880***
	(0.0477)	(0.0356)	(0.0350)	(0.0406)
acad_pat	0.164***			
	(0.00783)			
acad_pat*relatedness	-0.895***			
	(0.0512)			
n_acadpat		0.0571***		
		(0.00584)		
n_acadpat*relatedness		-0.523***		
		(0.0175)		
top_acadpat			0.128***	
			(0.00918)	
top_acadpat*relatedness			-0.960***	
			(0.0433)	
acad_inv				0.0589***
				(0.00416)
acad_inv*relatedness				-0.441***
				(0.0140)
share_newfirm	0.912**	1.048***	0.985**	1.037***
	(0.390)	(0.385)	(0.383)	(0.388)
S&Tgrad	-0.0103	0.00642	-0.00273	0.00180
	(0.00807)	(0.00822)	(0.00828)	(0.00819)
R&Duniv	-0.0134***	-0.00944***	-0.00959***	-0.0121***
	(0.00348)	(0.00363)	(0.00354)	(0.00356)
gdp	1.628***	1.624***	1.626***	1.610***
	(0.0394)	(0.0401)	(0.0393)	(0.0399)
empl	-1.341***	-1.322***	-1.330***	-1.320***
	(0.0409)	(0.0411)	(0.0407)	(0.0410)
Constant	1.171***	1.025***	1.096***	1.055***
	(0.123)	(0.123)	(0.123)	(0.124)
Observations	640,660	640,660	640,660	640,660
Number of tech-year	64,066	64,066	64,066	64,066
Year FE	Yes	Yes	Yes	Yes
chi2	10188	9742	10111	9611
p	0	0	0	0

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

8 Figures

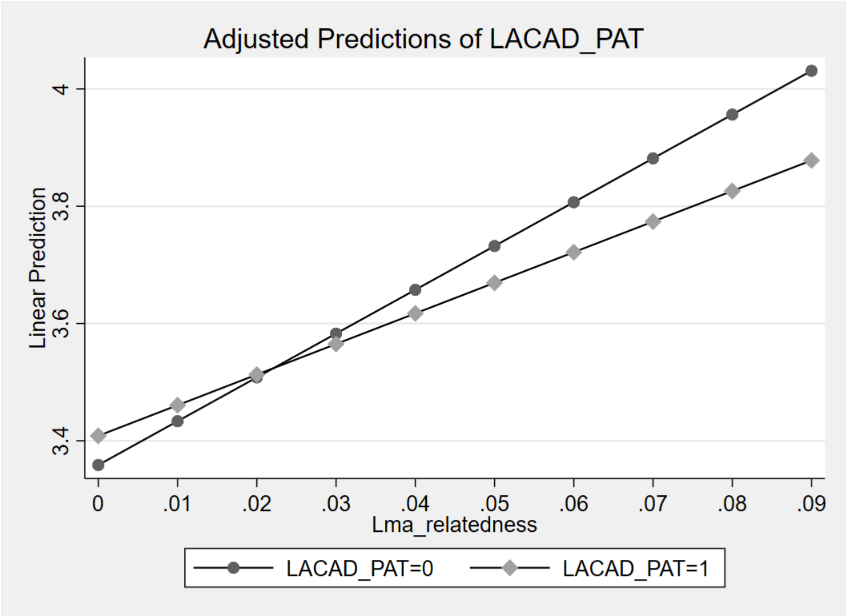

Figure 1: Interaction $acadpat_{it} * ma\_relatedness_{it}$

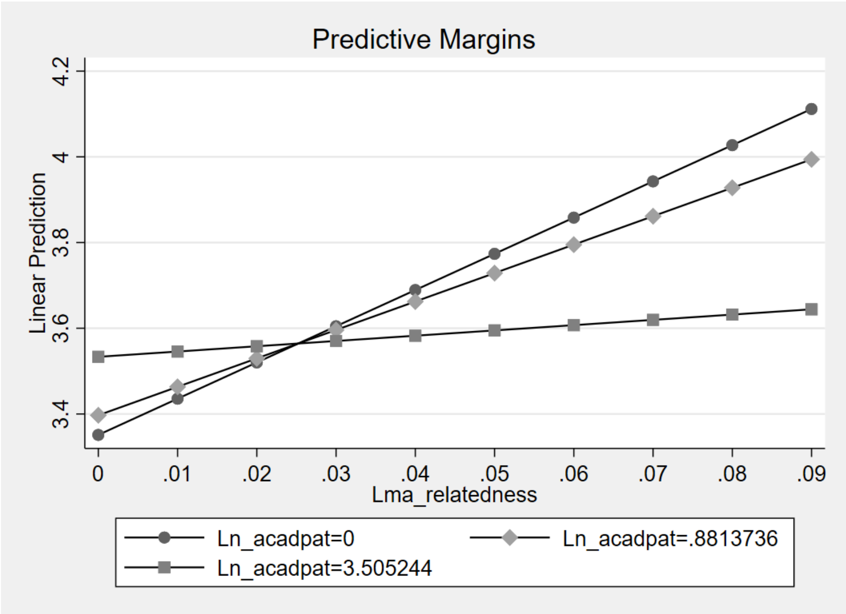

Figure 2: Interaction $n\_acadpat_{it} * ma\_relatedness_{it}$

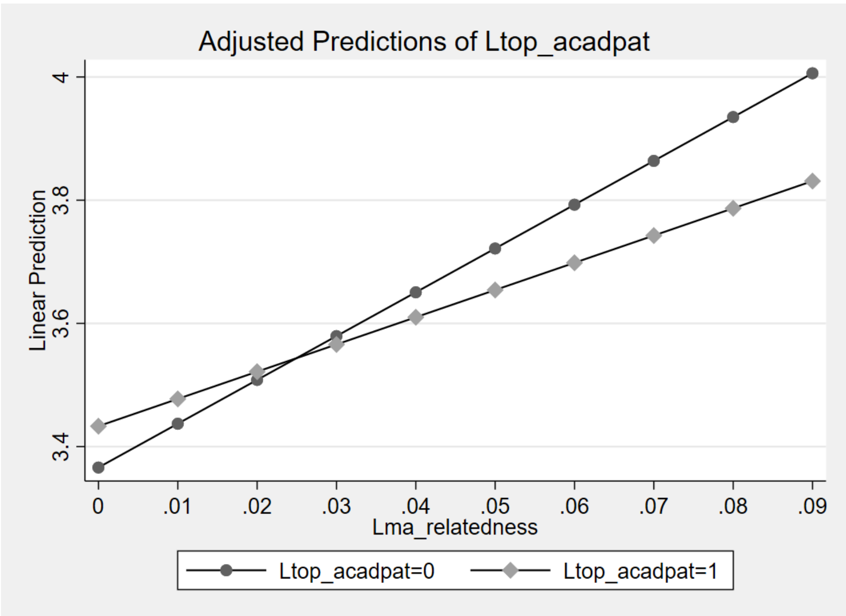

Figure 3: Interaction $top\_acadpat_{it} * ma\_relatedness_{it}$