New firm formation and regional knowledge production modes: Italian evidence

Published version:

DOI:10.1016/j.respol.2017.10.006

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ABSTRACT.

According to the knowledge-spillovers theory of entrepreneurship (KSTE), local knowledge spillovers affect entrepreneurial dynamics, because of knowledge asymmetries and uncertainty. Most of the empirical literature has tested this hypothesis using a measure of local knowledge stock. This paper is aimed at extending the framework by showing that the domains over which local knowledge spans are also important. The paper investigates the impact of the configuration of local knowledge bases on new firm formation dynamics by combining the KSTE framework with the recombinant knowledge approach. Local knowledge bases emerge from the combination of different knowledge inputs. These inputs may be closely or loosely related to one another. Technological differentiation and the relatedness degree of local competences can be interpreted as elements of the knowledge filter that affect the entrepreneurial absorptive capacity. The paper proposes a taxonomy of regional modes of knowledge production and investigates new firm formation in 92 Italian NUTS 3 regions observed over the 1995-2009 time span. The results confirm that the availability of local knowledge pools is important, and show that the 'rich integration' mode is the configuration that favours the entrepreneurial process. Finally, the policy implications and avenues for further research are presented and discussed.

Keywords: New Firm Formation, Knowledge-Spillovers Theory of Entrepreneurship, Recombinant Knowledge, Absorptive Capacity, Knowledge filter, Technological Relatedness, Variety.

JEL Classification Codes: L26, M13, R11, O33

1 Introduction

A large amount of literature has investigated the issue of "entrepreneurship" from different perspectives. One of the reasons for this interest is the belief that the creation of new firms constitutes one of the main engines of innovation and economic growth. Entry and exit dynamics are in fact the main drivers of industry turbulence (Audretsch, 1995). Their balance and economic impact varies according to the technological regime and across the evolutionary stages of an industry's lifecycle (Nelson and Winter, 1982; Winter, 1984).

Newborn firms are especially important in the entrepreneurial regime because they are likely to introduce innovations onto the markets, and above all radical technologies, thus contributing to economic growth (Aghion and Howitt, 1992; Wennekers and Thurik, 1999; Reynolds, 1999; Carree and Thurik, 2006; Audretsch et al., 2006).

However, the relationship between the formation of a new firm and its economic performance is not obvious, and is influenced by the economic context (Fritsch, 2013). Empirical analyses have addressed a wide range of dimensions related to the creation of new firms, in order to provide a better understanding of the factors that are conducive to entrepreneurial activities, and to understand the influence of the formation of new firms on economic growth. As discussed extensively in Vivarelli (2013) and in Quatraro and Vivarelli (2015), microeconomic analyses focus on the impact of firm size, credit rationing, education and learning dynamics, self-employment and innovation, whereas aggregate analyses tend to examine the shaping role of regional or national characteristics, as well as the effects of the new firm formation process on regional growth (Audretsch and Fritsch, 1994; Lee et al., 2004; Feldman, 2005; Acs et al., 2009; Delgado et al., 2010; Dejardin, 2011; Audretsch et al., 2012; Bishop, 2012; Qian et al., 2013). As far as macro level drivers are concerned, previous analyses stressed the importance of economic growth and innovative potential, as well as the features of the industrial structure involved in shaping the dynamics of new firm formation (Acs and Audrestch, 1989a and 1989b; Audretsch and Mahmood, 1995; Mata et al., 1995; Geroski, 1995; Audretsch et al., 1999)

As far as the analysis of new firm formation at a regional level is concerned, the Knowledge Spillovers Theory of Entrepreneurship (KSTE) has gained momentum over the last decade. The theory was first proposed in the seminal work by Audretsch (1995), and then formalized by Acs et al. (2009) as a refinement of endogenous growth models based on knowledge spillovers (Audretsch et al., 2015). KSTE posits that entrepreneurs should be viewed as the missing link between the generation of knowledge spillovers in local contexts and their economic exploitation. New ventures in this framework grasp the technological opportunities made available in the region, and which have been left unexploited by incumbent firms.

KSTE has found empirical support in a large number of regional level analyses of the determinants of new firm formation. In line with Griliches (1992), knowledge spillovers have been proxied in these studies considering the size of the knowledge stock that is locally available. However, little attention has so far been devoted to the fact that the local knowledge stock is the result of the research efforts of heterogeneous agents, whose activities can span a wide array of technological fields. However, how the composition of local knowledge bases can influence the effects of knowledge spillovers on the formation of new firms remains a somewhat less explored issue.

This paper has the aim of attempting to fill this gap and of contributing to the ongoing debate on the relationship between the features of local economic systems and new firm formation. Our approach is new in that it provides original theoretical and empirical frameworks to help understand knowledge-driven entrepreneurship. In our work, we stress that local knowledge pools are the result of a combinatorial search activity carried out in a technological space in which combinable elements reside (Weitzman, 1998; Fleming, 2001; Fleming and Sorenson, 2001). Therefore, knowledge spillovers do not automatically generate new entrepreneurial opportunities. Basic dimensions, such as technological differentiation and the relatedness degree of local technological activities. are likely to affect the effectiveness of the transformation of knowledge spillovers into new ventures (Saviotti, 2007; Quatraro, 2010). We propose that these dimensions can qualify and extend the knowledge filter concept, i.e. the set of factors that can boost or create a barrier to the actual commercial exploitation of local knowledge spillovers (Acs and Plummer, 2005; Braunerhjelm et al., 2010). We elaborate a taxonomy of regional knowledge production modes and formulate the hypothesis that high levels of technological differentiation and relatedness reduce knowledge asymmetries and uncertainty, and are associated with high levels of new firm formation dynamics at the local level.

According to most of the studies in the KSTE literature, our analysis has focused on the patterns of new firm formation in the high-technology (HT) and medium-high-technology (MHT) sectors, in the Italian NUTS 3 region context (i.e. the “provincial” level) over the 1995-2009 period. This choice is appropriate for our analysis for various reasons. First, the close relationship between the entrepreneurial process and local economies calls for focus on a rather narrow definition of region, but large enough to statistically represent a region of knowledge spillovers (Audretsch and Lemann, 2005). Second, the Italian economy appears to be stuck in mature industries, and is significantly lagging behind, from a technological viewpoint, compared to most of the other advanced countries (Quatraro, 2009a,b).

The results of the analysis are in line with KSTE and confirm that knowledge spillovers trigger the creation of new firms in local contexts. Moreover, when the composition of local knowledge bases is taken into account, the econometric analysis shows that the degree of technological relatedness and differentiation of the technological domains in the region have a positive effect on the formation of new firms, with the impact of differentiation in the related technological domains being stronger than that in the unrelated ones. This provides support for the hypothesis that high levels of technological relatedness mitigate the impact of knowledge asymmetries and uncertainty.

The rest of the paper is organized as follows. Section 2 discusses the theoretical bases that underpin the relationship between new firm formation, local innovation and recombinant knowledge, while Section 3 outlines our hypotheses. We present the research design and describe the data, the variables and the methodology in Section 4 while we present the results of the econometric analysis in section 5. Finally, section 6 offers some concluding remarks and policy implications.

2 New firm formation, KSTE and recombinant knowledge

2.1 Spatial dynamics, entrepreneurship and KSTE

The investigation of the determinants and effects of entrepreneurship has mainly focused on the geographical dimension of this phenomenon. On one hand, empirical studies have pointed out the positive impact of new firm formation on regional growth and competitiveness (Audrestch and Fritsch, 1996; Fritsch and Schindele, 2011; Fritsch, 2013).

On the other hand, compelling evidence has emerged concerning the spatial dynamics of new firm formation and the enabling role of local factors. Variables such as population density, population growth, skills and human capital levels of the labor force have been found to positively affect entrepreneurial activity at the regional level (Reynolds, Storey and Westhead 1994)[1]. Other studies have instead stressed the importance of the local availability of venture capital, supportive social capital, research universities and support services for entrepreneurship (Feldman, 2001).

In this framework, and in line with the works by Porter (1998) and Saxenian (1994 and 1999), special attention has been paid to agglomeration economies and local externalities as the driving forces behind the geographical distribution of entrepreneurial dynamics (Breshanan et al., 2001; Feldman, 2001 and 2005). Lee et al. (2004) extended the notion of Jacobs externalities to investigate the importance of social diversity and creativity on the formation of new firms.

[1] The Regional Studies journal published a special issue on “Regional Variations in New Firm Formation” in 1994, where empirical papers that had investigated these aspects by focusing on European evidence were presented.

Audretsch et al. (2012), considering the Marshallian intuition, showed that the local environment shapes the process of entrepreneurship, particularly in terms of regional regimes grounded in accumulated entrepreneurial culture. Similarly, Delgado et al.'s (2010) empirical analysis pointed out the impact of knowledge externalities and agglomeration on regional entrepreneurial dynamics. Stam (2007) argued that the interlinking between the features of local clusters and the location choices of newborn firms evolves over a firm's lifecycle, so that some local aspects, such as the availability of an established network of relations, are more important in the early stages, while others are more important in the later stages.

KSTE deals with the contextual variables that influence entrepreneurship, and in particular points out the importance of local knowledge spillovers, not only for the competitiveness of new ventures but also for the very process of new firm formation (Audretsch et al., 2015).

This theory is elaborated as a refinement of endogenous growth models, in which knowledge spillovers are considered as key drivers of sustained growth. Spillovers exist because knowledge is an inappropriable and non-rival commodity, so that the aggregate economic impact of knowledge production is larger than the firm-level impact (Arrow, 1962b; Griliches, 1992). KSTE criticizes the way knowledge is conceptualized in new growth theories, according to which the economic impact of knowledge spillovers is automatic and ubiquitous. This criticism is based upon Arrow’s (1962a) argument, according to which not all produced knowledge is economically useful. Knowledge that is produced in local contexts and which spills over third parties needs substantial efforts and the commitment of resources to be transformed into productive knowledge. Prospective entrepreneurs can play a key role in this process, by taking advantage of the profit opportunities engendered by the local knowledge that is left unexploited by incumbents (Acs et al., 2009).

The reasons why some knowledge stays untapped, and hence knowledge spillovers can represent a source of entrepreneurial opportunities, are ascribed to the inherent features of knowledge as a type of economic goods (Arrow, 1962b). In this respect, the basic dimensions are the degree of uncertainty, the importance of asymmetries and the cost of transacting new ideas (Rosenberg, 1996; Audretsch et al., 2015). Uncertainty concerns the expected value of knowledge, while knowledge asymmetries and transaction costs are instead related to the difficulties involved in the correct screening of the feasibility, originality and the potentials of new ideas. For these reasons, incumbent firms might not decide to follow on or commercialize new ideas that other individuals or groups might consider as potentially valuable (Acs et al., 2009; Audretsch et al., 2006). In this framework, public or private organizations that develop new knowledge with potential on the markets, but which decide not to commercialize it, are labeled as 'knowledge incubators' (Audretsch et al., 2009).

Empirical analyses have been conducted to investigate and provide support concerning the impact of local knowledge spillovers on the entrepreneurial process. In these studies, the locally available stock of knowledge is the key variable, and it is usually proxied either by R&D investments (Audretsch and Keilbach, 2007), or by the research efforts carried out in co-localized universities and research centers (Audretsch and Lehmann, 2005; Cassia et al., 2009; Cassia and Colombelli, 2008; Bonaccorsi et al., 2013).

However, the presence of 'knowledge incubators', and hence of unused knowledge pools, can be considered as a necessary, but not sufficient, condition for the actual exploitation of such entrepreneurial opportunities for at least two reasons, as identified in the extant literature. First, the transformation of knowledge stocks into economically useful knowledge requires the presence of enabling conditions at the local level. These conditions pertain to the existence of supporting institutions, knowledge intermediaries, regulatory frameworks and appropriate financial markets. The absence of these conditions could create a barrier that hinders the transformation of knowledge into economic knowledge *à la Arrow*. Such a barrier has been referred to as a 'knowledge filter' (Acs et al., 2004; Acs and Plummer, 2005). New firms may serve as a conduit for knowledge spillovers, insofar as the features of local contexts allow them to penetrate the knowledge filter.

This concept encompasses the basic characteristics of knowledge set forth by Arrow (1962a), although it is broader in scope. According to Audretsch (2007), it is the outcome of "the characteristics of knowledge distinguishing it from information, a high degree of uncertainty combined with non-trivial asymmetries, combined with a broad spectrum of institutions, rules and regulations" (Audrestch, 2007: p.67). Therefore, the knowledge filter generates a gap between the creation of knowledge and its commercialization through the establishment of new ventures.

Second, it is worth mentioning that the basic characteristics of knowledge also imply that prospective entrepreneurs are endowed with differential absorptive capacity. Qian and Acs (2013) proposed an absorptive capacity theory of entrepreneurship, according to which new firm formation may serve as a mechanism to commercialize untapped knowledge, depending on "the ability of an entrepreneur to understand new knowledge, recognize its value and commercialize it by creating a new firm" (Qian et al., 2013: p. 563).

In short, the KSTE-related literature discussed so far implies that regional variations in the availability of knowledge are associated with differential rates of new firm formation. However, a local abundance of knowledge does not necessarily lead to its commercialization through new ventures. Regional variations, in terms of supporting institutions, regulations and entrepreneurial absorptive capacity, may in fact create a filter that affects the likelihood of prospective entrepreneurs actually succeeding in exploiting the market opportunities provided by unexploited knowledge. Figure 1 provides a synthetic illustration of these dynamics.

>>> INSERT FIGURE 1 ABOUT HERE <<<

The knowledge filter and entrepreneurial absorptive capacity both help to understand the regional differences in the relationship between knowledge spillovers and new firm formation.

Most of the extant works in the KSTE tradition have adopted proxies to investigate the impact of the size of knowledge spillovers on new firm formation. Such an approach regards local knowledge spillovers as an undifferentiated stock, but fails to acknowledge the heterogeneity of knowledge producing agents or the very mechanisms of knowledge production, which are based on a combination of existing knowledge in new ideas (Saviotti, 2007).

A few exceptions can be found in the literature. For example, Bae and Koo (2008) focused on communication equipment and electronic component accessory industries, and they explored the patenting dynamics in a region in order to derive variety and relatedness measures. The former was obtained by calculating the Herfindal index for the knowledge fields of the United States Patent and Trademark Office (USPTO). The latter was calculated by looking backward at patent citations in order to measure the extent to which entry into the sector under scrutiny was shaped by the presence of knowledge in fields that were closely related to the firm's underlying competences. Bishop (2012) suggested some proxies for knowledge stock and variety, which were measured as the regional share of employment in knowledge-based industries and informational entropy grounded in sectoral employment, respectively. Colombelli (2016) has shown that local variety and similarity may affect the rate of creation of innovative startups.

These recent studies have pointed out, in different ways, the importance of the heterogeneous nature of knowledge to qualify local knowledge pools in the investigation of knowledge-based entrepreneurship. The distribution of local knowledge production activities across different domains, and the degree of relatedness among them may in fact shape the effectiveness of knowledge-based entrepreneurial dynamics. For this reason, we introduce the recombinant knowledge theory in the next section, as it might lead to a useful integration in this respect.

2.2 The recombinant knowledge approach

The recombinant knowledge approach originates from the seminal work by Weitzman (1996, 1998). In this framework, new ideas are considered as being generated through the recombination of existing ideas, under the constraint of diminishing returns-to-scale in the performance of the research and development (R&D) activities necessary to apply new ideas to economic activities (Caminati, 2006).

A stream of contributions that have fed the debate, from manifold perspectives, has emerged from these insights. For example, Kauffman (1993), applied the N-K model and maintained that the success of a search process depends on the topography of a given knowledge landscape, which in turn is shaped by the complementary relations (K) among the different elements (N) of a given unit of knowledge.

Fleming and Sorenson (2001) tested the hypothesis put forward by Kauffman, according to which the likelihood of success depends on the characteristics of the technological landscape in which the search process takes place. Further extensions of the framework have been proposed by Olsson (2000) and Olsson and Frey (2002), who introduced the notion of technological space and elaborated the costs of knowledge recombination.

Recent contributions in the evolutionary economics field have integrated the recombinant knowledge approach with a theoretical framework with the aim of shedding new light on the dynamics of knowledge generation. In these contributions, knowledge is conceptualized as a co-relational structure in which the similarity and complementarity degree of its constituting parts qualifies its internal configuration (Saviotti, 2004 and 2007). This framework has been adopted extensively to qualify the knowledge base of firms, sectors and regions, and to investigate the impact of the average level of technological differentiation, complementarity and similarity on different performance indicators, such as productivity, sales growth and innovation (Antonelli et al., 2010; Quatraro, 2010; Krafft et al., 2011 and 2014; Colombelli et al., 2014; Colombelli, 2016).

It is possible to represent the knowledge base of a firm, a sector or a region, as a web of connected elements by adopting the recombinant knowledge approach. The nodes of this network represent the elements of the knowledge space that can be combined, while the links represent their actual combination. This allows some interesting properties of a specific knowledge base that reflect the direction of the innovation efforts of local agents to be identified at a regional level. The degree of technological differentiation of the knowledge base, and the complementarity of the array of local technological domains, in this respect provide a synthetic account of the relatedness degree of the constituting elements of the knowledge base.

3 Development of the hypotheses

The present study has had the aim of taking a step forward by focusing on the link between the configuration of local knowledge bases and the ability of prospective entrepreneurs to create new ventures by grasping the opportunities provided by the unexploited knowledge that is available at the local level.

From a theoretical viewpoint, we propose that the traditional KSTE arguments could benefit from an extension that takes into account the inherent heterogeneous nature of locally available technological knowledge. Along these lines, the integration of the recombinant approach in KSTE could be far reaching.

The recombinant approach allows some qualification of the arguments proposed in KSTE to be made, by explicitly taking into account the role played by the degree of relatedness and differentiation in the technological domains that feature the local knowledge base.

Specific configurations of the local knowledge base can represent a barrier to the actual exploitation of knowledge spillovers by prospective entrepreneurs, while other configurations may result to be more suitable. In other words, the composition of the knowledge stock can be regarded as a dimension of the knowledge filter (Acs and Plummer, 2002; Acs et al., 2004; Audretsch et al., 2006), i.e. a factor that creates a gap between the creation of new knowledge and its commercialization by newborn firms.

According to the principles of evolutionary economics, variety can be expected to positively affect the capacity of local innovation systems to generate new knowledge (Nelson and Winter, 1982; Saviotti, 1988). The higher the degree of technological differentiation, the larger the amount of knowledge produced at the local level. All other things being equal, an increasing amount of knowledge should translate into greater opportunities for prospective knowledge-based entrepreneurs.

Technological differentiation leads to the generation of new knowledge through recombination dynamics. In this process, the degree of complementarity, or relatedness, among technologies is of paramount importance in shaping the effectiveness of combinatorial activities. Previous literature showed that the higher the relatedness degree of combined technologies, the higher the innovative potential of firms or regions (Nesta, 2008; Quatraro, 2010). Innovating agents engage in successful recombination dynamics insofar as they process knowledge inputs that are close to their competences, and they show a high degree of interoperability and compatibility. The availability of local knowledge pools is therefore related to the configuration of local knowledge bases, which in turn affects the entrepreneurial opportunities.

Moreover, the higher the degree of internal coherence of the local knowledge, i.e. the relatedness degree of its components, the better the entrepreneurial absorptive capacity, which partly contributes to the formation of the local knowledge bases themselves. At the regional level, provided the knowledge activities are distributed across highly complementary technological fields, prospective entrepreneurs are likely to be endowed with the appropriate competences that allow them to effectively command and commercialize unused knowledge by reducing knowledge asymmetries and uncertainty.

In view of these arguments, the configuration of local knowledge bases is proposed as an additional dimension of the knowledge filter that shapes both contextual factors and entrepreneurial absorptive capacity. The diagram presented in Figure 1 is accordingly extended in Figure 2.

>>> INSERT FIGURE 2 ABOUT HERE <<<

On the basis of these grounds, by combining the two key dimensions of a knowledge base configuration, i.e. variety and relatedness, it is possible to elaborate a taxonomy of regions in which the modes of knowledge production are related to knowledge-based entrepreneurship. Figure 3 identifies four quadrants. The top quadrant regions feature a low technological variety and, due to the arguments discussed above, are more likely to exhibit poor knowledge-based opportunities. On the other hand, the bottom quadrant regions are rich in opportunities for knowledge-based entrepreneurship, as a result of high levels of variety. The knowledge base of regions in the left quadrants along the horizontal axis is characterized by a dispersion of innovation activities across unrelated technological domains. This is likely to favor the emergence of knowledge asymmetries and uncertainty, thus making the absorption and evaluation of the available economic potential more difficult. On the other hand, the right quadrant regions feature a highly coherent and integrated knowledge base. In these contexts, knowledge asymmetries are mitigated and uncertainty is reduced. Moreover, it is much more likely that the competences of prospective entrepreneurs are complementary to the local knowledge pools. This eases the absorption, the correct screening, evaluation and the commercialization of untapped knowledge.

>>> INSERT FIGURE 3 ABOUT HERE <<<

By combining the two dimensions, the different knowledge-based entrepreneurship contexts can be labeled as i) poor dispersion; ii) poor integration; iii) rich dispersion; iv) rich integration. The latter configuration seems to provide the most favorable conditions for the emergence of knowledge-based entrepreneurship, provided there is an impact on local knowledge production activities and on knowledge asymmetries and uncertainty.

According to these arguments, it is possible to formulate the following hypothesis:

H1. *The creation of new firms is affected by the local availability of knowledge spillovers, so much so that the greater the amount of available local knowledge, the higher the number of new firms.*

This hypothesis summarizes the traditional KSTE argument concerning the relationship between new knowledge and entrepreneurship, as discussed in Section 2.1.

As pointed out in Section 3, the configuration of the local knowledge bases, in terms of technological variety and relatedness of the observed technological fields, constitutes a dimension of the knowledge filter that can influence the dynamics of new firm formation. On the basis of these extensions and qualifications of the KSTE framework, the following hypotheses can be proposed.

H2: *Regions that feature high levels of knowledge variety can be expected to show high rates of new firm formation, because of the larger number of technological opportunities.*

H3: *Regions that feature high levels of relatedness can be expected to show high rates of new firm formation, because of the mitigation of knowledge asymmetries and uncertainty, and the enhancement of entrepreneurial absorptive capacity.*

The next section provides details concerning the data, variables and econometric strategy that have been considered to test these hypotheses.

4 Research Design

The basic hypotheses formulated in section 3 state that the properties of the local knowledge base act as a filter for the dynamics of new firm formation from the KSTE perspective. The empirical test of our hypotheses was carried out on a sample of Italian NUTS 3 regions. The focus on a within-country sample of regions allows some of the problems of heterogeneity and omitted variables to be mitigated, above all those concerning the institutional setting, and in particular those related to the implementation of specific programs to promote entrepreneurship. Moreover, given the local dimension of knowledge spillovers, NUTS 3 regions represent a sufficiently large geographic area to statistically represent a region of knowledge spillovers (Audretsch and Lemann, 2005).

4.1 The Data

In order to implement our empirical analysis, we considered the (net) number of new businesses registered for value added tax (VAT). These data were provided by the Union of the Chambers of Commerce (Unioncamere) and were taken from the Movimprese dataset. These statistics exclude certain types of entrepreneurial activities that are not subject to compulsory registration with the Chamber of Commerce, i.e. 'small entrepreneurs' - mainly artisans, or small businesses based exclusively on the work of the members of the family that owns the business, or sharecrop farmers. For the purposes of the present study, this exclusion has allowed us to eliminate "necessity entrepreneurs", for whom local knowledge spillovers are unlikely to be relevant, from the analysis.

As far as the properties of local knowledge bases are concerned, we matched the OECD RegPat Database (July 2012) with Eurostat data and NUTS3-level[2] data provided by the Italian institute of statistics (ISTAT) - "Indicatori territoriali per le politiche di sviluppo" (local indicators of development policies). The OECD's RegPat database is derived from the Patstat database, which ensures worldwide coverage; it includes bibliographic patent data, citations and family links. These data include applications to the European Patent Office (EPO) and applications to national patent offices that go back as far as 1920 in the case of some patent authorities. This overcomes the limitations of EPO data due to its relatively young age.

Patent applications are regionalized at the NUTS 3 level on the basis of the inventors' addresses. Applications in which several inventors reside in different regions are assigned to the relevant regions according to their respective shares. Our study has been limited to applications submitted by

[2] The analysis covers the 1995-2009 period. The Italian NUTS 3 classification changed in 2006 and 2009, with the addition of 4 and 3 new regions, respectively. In order to ensure coherence in the dataset, we used the pre-2006 classification. This only posed a problem for the Barletta-Andria-Trani region, which now includes 7 municipalities that were previously part of the Bari province, and 3 municipalities that were previously part of the Foggia province. No data were available at a municipality level, so it was not possible to overcome this issue.

inventors residing in Italian regions, and has used the International Patent Classification (IPC), maintained by EPO, to assign applications to technological classes.

4.2 The Variables

4.2.1 Dependent Variable

Audretsch and Fritsch (1994) pointed out that the choice of the dependent variable is not neutral in the firm creation context, and they identified two alternative approaches, that is, the ecological approach and the labor market approach. They showed that these approaches can yield very different results when implemented in empirical settings characterized by the same exogenous variables. The ecological approach standardizes figures on new firm creation by using the stock of existing firms, while the labor market approach uses employment levels.

In their studies, Audretsch and Lehman (2005) and Bonaccorsi et al. (2013) assumed that new firms, in local contexts, can be interpreted as count data. We have adopted this approach and used the count of new firms in each province at time t ($NEWFIRMS_{i,t}$) as the dependent variable[3].

Since we are interested in the impact of the local knowledge base on new firm formation, we need a narrower perspective of the involved sectors. In line with most of the empirical analyses in this strand, and as discussed in Section 2, we have in particular focused on newborn firms in the High-technology (HT) and Medium-High-Technology (MHT) manufacturing sectors. This classification was first proposed by ISTAT, and is based on the Eurostat/OECD classification. The correspondence between the two groups and the NACE rev.1.1 classification can be found in APPENDIX B.

Figure 4 shows the distribution of newborn firms and the stock of firms in the HT and MHT sectors across the Italian NUTS 3 regions[4].

[3] However, we do not deny that local markets are not sized similarly, and this could introduce some biases into our results. For this reason, as we specify hereafter, we have introduced the employment level in/of the province among the control variables.

>>> INSERT FIGURE 4 ABOUT HERE <<<

The diagram is characterized by marked spatial clustering dynamics in which a distance decay is quite evident. Some regions exhibit very high rates of new firm formation (Figure 4a), while the dynamics in contiguous regions may be slightly less marked. The further one moves away from those highly entrepreneurial regions, the lower the rates of new firm formation. Interestingly, these dynamics apply to the North, Center and South of the country. They also seem to be persistent in relation to the stock of firms rather than newborn firms (Figure 4b).

4.2.2 The Implementation of Knowledge Indicators[5]

Testing the baseline KSTE argument involves using a measure for the local knowledge stock. This can be either an input or an output measure. The former could refer to local expenditure on R&D to proxy the pool of available technological knowledge (Acs et al., 2009). Unfortunately, no data were available on R&D expenditure at the NUTS 3 level in Italy. Therefore, we adopted an output measure, i.e. a local knowledge stock (KSTOCK), which was calculated on patent applications, applying the permanent inventory method as follows. We calculated the cumulated stock of past patent applications using a rate of obsolescence of 15% per annum[6]:

$$KSTOCK_{i,t} = \dot{h}_{i,t} + (1-\delta)KSTOCK_{i,t-1}, \qquad (1)$$

where $\dot{h}_{i,t}$ is the flow of patent applications, δ is the rate of obsolescence[7], i is the region and t is the time period.

[4] 4 Four Sardinian provinces are not shown on the map since no data were available for them.
[5] This section builds on Krafft et al., (2014); Colombelli et al., (2013); and Quatraro (2010).
[6] The choice of the rate of obsolescence raises some basic issues as to which is the most appropriate value. There are in fact a number of studies, ranging from that of Pakes and Schankerman (1989) to that of Schankerman (1998), that attempted to estimate the patent depreciation rate. However, for the scope of this paper, we have followed the established body of literature based on Hall et al. (2005) that applies the same depreciation rate to patent applications as the one applied to R&D expenditures (see, for example, McGahan and Silverman 2006, Coad and Rao 2006, Nesta 2008, Laitner and Stolyarov 2013, Rahko 2014).
[7] A similar approach was adopted in Soete et Patel (1985).

In section 2.3, we propose looking at the degree of relatedness and variety in the technological domains that feature the local knowledge base as a filtering dimension to the mechanisms articulated in KSTE. In order to operationalize these dimensions, we followed an approach based on information contained in patent documents[8]. In this way, we were able to calculate a number of variables that characterize the local knowledge base, such as the coherence and degree of variety of its components.

We considered patents as proxies of knowledge, and looked at the technological classes to which patents were assigned as the constituting elements of their structure. Each technological class *j* was linked to another class *m*, if the same patent was assigned to both of them[9]. The higher the number of patents assigned to both the *j* and *m* classes, the stronger this link. Since technological classes attributed to patents are reported in the patent document, we refer to the link between *j* and *m* as their co-occurrence within the same patent document[10].

On this basis, we were able to calculate the following two key characteristics of a region's knowledge base:

a) Knowledge variety (KV) measures the degree of technological diversification of the knowledge base. It is based on the informational entropy index;
b) Knowledge coherence (COH) measures the average degree of relatedness of the technologies that make up the regional knowledge base.

[8]The limitations of patent statistics as indicators of technological activities are well known. The main drawbacks include their sector-specificity, the existence of non-patentable innovations, and the fact that they are not the only protection tool. Moreover, the propensity to patent tends to vary over time as a function of the cost of patenting, and it is more likely to affect large firms (Pavitt, 1985; Griliches, 1990). Nevertheless, previous studies have highlighted the usefulness of patents as measures of the production of new knowledge. These studies show that patents represent very reliable proxies of knowledge and innovation, compared to analyses that draw on surveys which directly investigate the dynamics of process and product innovation (Acs et al., 2002). Apart from the debate on patents as an output rather than an input of innovation activities, empirical analyses have shown that patents and R&D are dominated by a contemporaneous relationship, thus providing further support for the use of patents as a good proxy of technological activities (Hall et al., 1986).

[9] The calculations use 4-digit technological classes. We have also checked the robustness of our analyses by implementing the calculations using a 7-digit classification. The results are consistent, and the thus obtained tables are available from the authors on request.

[10]It should be pointed out that to compensate for the intrinsic volatility of patenting behavior, each patent application was repeated for 5 years in order to reduce the noise induced by changes in technological strategy.

4.2.2.1 Knowledge variety

Knowledge variety has been measured using the information entropy index[11]. Entropy measures the degree of disorder or randomness of a system; systems characterized by high entropy are characterized by high degrees of uncertainty (Saviotti, 1988). Informational entropy is a diversity measure which allows variety to be taken into account, i.e. the number of categories into which the elements of a system are apportioned, and also balanced, i.e. the distribution of system elements across categories. (Stirling, 2007).

Information entropy has some interesting properties (Frenken and Nuvolari, 2004), one of which is multidimensionality. This is particularly relevant for the purposes of this research, since it has allowed us to build an entropy index of the distribution of the co-occurrences of technological classes in patents rather than the distribution of single technological classes. This approach is different from that implemented in most of the studies that are based on the work of Frenken et al. (2007) in which a unidimensional entropy is calculated to proxy the variety of industrial activities in a region. Our focus on co-occurrences of technological classes captures the variety of combinations of knowledge inputs and is consistent with the recombinant knowledge framework introduced in section 2, according to which what matters, as far as knowledge creation is concerned, is the combination pattern of the different pieces of knowledge.

Let us consider a pair of events (X_l, Y_j), and the probability of their co-occurrence p_{lj}. A two-dimensional total variety (*TV*) measure can be expressed as follows:

$$KV \equiv H(X,Y) = \sum_{l} \sum_{j} p_{lj} \log_2 \left(\frac{1}{p_{lj}} \right) \quad (2)$$

[11] For the sake of clarity, region and time indexes have been omitted.

Let the events X_l and Y_j be citations in a patent document of technological classes *l* and *j*, respectively. Therefore p_{lj} is the probability that two technological classes *l* and *j* co-occur within the same patent. Therefore, the measure of multidimensional entropy focuses on the variety of co-occurrences or pairs of technological classes in patent applications, and provides an index of how much the creation of new knowledge is focused on a narrower set of possible combinations.

The total index can be decomposed into 'within' and 'between' parts, whenever the events being investigated can be aggregated into a smaller number of subsets. Within-entropy measures the average degree of disorder or variety within the subsets; between-entropy focuses on the subsets, measuring the variety across them. Let the technologies *i* and *j* belong to the subsets *g* and *z* of the classification scheme, respectively. If one allows $l \in S_g$ and $j \in S_z$ (g = 1,…,G; z = 1,…, Z), it is possible to write:

$$P_{gz} = \sum_{l \in S_g} \sum_{j \in S_Z} p_{lj} \tag{3}$$

which is the probability of observing the couple lj in the subsets *g* and *z*, while the intra subsets variety can be measured as follows:

$$H_{gz} = \sum_{l \in S_g} \sum_{j \in S_z} \frac{p_{lj}}{P_{gz}} \log_2 \left(\frac{1}{p_{lj}/P_{gz}} \right) \tag{4}$$

The (weighted) within-group entropy can therefore be written as follows:

$$RKV \equiv \sum_{g=1}^{G} \sum_{z=1}^{Z} P_{gz} H_{gz} \tag{5}$$

Between group (or unrelated variety) can instead be calculated using the following equation:

$$UKV \equiv H_Q = \sum_{g=1}^{G} \sum_{z=1}^{Z} P_{gz} \log_2 \frac{1}{P_{gz}} \tag{6}$$

According to the decomposition theorem, the total entropy *H(X,Y)* can be re-written as follows:

$$KV = H_Q + \sum_{g=1}^{G} \sum_{z=1}^{Z} P_{gz} H_{gz} \tag{7}$$

Within-group entropy (or related variety) measures the degree of technological differentiation within the macro-field, while between-group variety (or unrelated variety) measures the degree of technological differentiation across macro-fields. The first term on the right-hand-side of equation (7) is the between-entropy and the second term is the (weighted) within-entropy.

We have labeled between- and within-entropy as *unrelated technological variety* (*UKV*) and *related technological variety* (*RKV*), respectively, while total information entropy is referred to as *general technological variety* (Frenken et al., 2007; Boschma and Iammarino, 2009). This means that we consider variety as a global entity, but also as a new combination of existing pieces of knowledge *versus* variety as a combination of new pieces of knowledge. When variety is high (respectively low), the search process becomes extensive (respectively partial). When unrelated variety is high, compared to related variety, the search process is essentially based on a combination of novel pieces of knowledge rather than new combinations of existing pieces of knowledge.

4.2.2.2 Knowledge coherence

We have calculated the coherence of NUTS3 region knowledge bases, defined as the average relatedness or complementarity of a technology chosen randomly from the region's patent portfolio with respect to any other technology (Nesta and Saviotti, 2006; Nesta, 2008; Quatraro, 2010).

Obtaining the knowledge coherence index involved a number of steps. First, we needed to calculate the weighted average relatedness WAR_l of technology l with respect to all the other technologies in the regional patent portfolio. This measure builds on the *technological relatedness* measure among any pair of technologies i and j, τ_{lj} (see appendix A for details of the calculation).

According to Teece et al. (1994), the weighted average relatedness, WAR_l is defined as the degree to which technology l is related to all other technologies $j \neq l$ in the region's patent portfolio, weighted by patent count P_{jt}:

$$\mathrm{WAR}_{lt} = \frac{\sum_{j \neq l} \tau_{lj} P_{jt}}{\sum_{j \neq l} P_{jt}} \tag{8}$$

Finally, the coherence of the region's knowledge base at time t is defined as the weighted average of the WAR_{lt} measure:

$$COH_t = \sum_{l} \mathrm{WAR}_{lt} \times \frac{P_{lt}}{\sum_{l} P_{lt}} \tag{9}$$

It should be noted that this index is implemented by analyzing the co-occurrence of technological classes within patent applications, it measures the degree to which the services rendered by the co-occurring technologies are complementary, and it is based on how frequently technological classes are combined in use. The relatedness measure τ_{lj} indicates that the utilization of technology l also implies the use of technology j, in order to perform specific functions that are not reducible to their independent use[12].

4.2.3 Control variables

Apart from the effects of the knowledge indicators, we have also controlled for a number of factors that the theory identifies as having a possible effect on new firm formation.

First, the possibility of reaping the economic benefits that stem from unexploited local knowledge is shaped by the extent firms and people are geographically clustered, since proximity enhances knowledge flows amongst innovating agents. For this reason, we have controlled for the effects of agglomeration economies using two different but complementary measures. First, we included

[12] According to Engelsman and van Raan (1994), this approach produces meaningful results, particularly at the 'macro' level, i.e. to map the entire technology domain.

population density (POP_DENS) at the NUTS 3 level. This is/was calculated by dividing the total population at time *t* in region *i* by the land use area:

$$POP\_DENS_{i,t} = \frac{POP_{i,t}}{AREA_i} \tag{10}$$

A complementary measure of prospective economic benefits is also represented by the distance (DIST) of each province *i* from the main administrative town in the NUTS 2 region (Baptista and Mendonça, 2010; Bonaccorsi et al. 2013).

Second, the density of incumbent firms in a geographical area has been shown to significantly affect the creation of new firms at the local level as a source of knowledge spillovers (e.g., Baptista and Swann 1999; Bonaccorsi et al., 2013). For this reason, we have also included firm density (FIRM_DENS), calculated as the ratio between the number of registered firms in medium and high-technology sectors at time *t* in region *i* and the land use area, as a control variable:

$$FIRM\_DENS_{i,t} = \frac{FIRMS_{i,t}}{AREA_i} \tag{11}$$

Third, the features of the industrial structure may also shape the dynamics of firm formation. In this respect, the sectoral composition of local economies is a crucial factor (Quatraro and Vivarelli, 2015). In order to control for industrial structure, we have followed the approach of Bonaccorsi et al. (2013) and included a measure of industrial diversity (IND_DIV) at time *t* in region *i*, proxied by the Herfindal-Hirschman index of the shares of incumbent firms in each industry. The 2-digit ATECO 2002 classification was used for this purpose.

Fourth, we have calculated the number of incubators (INC) in each province. Business incubators represent a key resource for the creation of new firms, provide the conditions necessary for successful undertakings and increase the survival likelihood (Colombo and Delmastro, 2002; Peters, Rice, & Sundararajan, 2004; Rice, 2002; Auricchio et al., 2014).

Fifth, consistent with the labor market approach to the measurement of entrepreneurship (Audretsch and Fritsch, 1994), we have included the employment level in the manufacturing sector (MANEMPL) at time *t* in region *i*.

Sixth, a large body of literature has underlined the importance of international trade, and in particular of exports, for the creation of new ventures. High degrees of internationalization may engender the dynamics of 'learning by exporting', based on knowledge about new market and technological opportunities flowing from foreign countries (Blalock and Gertler; 2004; Branstetter 2006; Hessels and van Stel, 2011). For this reason, we have included a variable that controls for the internationalization degree of the NUTS3 region *i* at time *t* in the analysis. The variable (OPENNESS) was taken from the Italian Institute of Statistics (ISTAT), and was calculated as the share of the value of regional exports in 'dynamic' sectors over the total exports[13].

Seventh, limited access to financial resources may hamper the entrepreneurial process (Blumberg and Latterie, 2007). Credit rationing is based on information asymmetries, according to which banks may experience difficulties in screening investments projects in new ventures, and hence in determining whether a project is a good or bad risk. This engenders a supply shortage for prospective entrepreneurs that cannot rely on personal wealth (Stiglitz and Weiss, 1981; Evans and Jovanovic, 1989; Johansson, 2000). In line with this literature, we have included a variable (FIN_SYSTEM) in the econometric model that controls for the quality of the financial markets in NUTS 3 regions, which has been proxied by the rate of decay of investments.

Eighth, the average size of local incumbents is also likely to shape the dynamics of new firm formation. However, such a relationship can be ambiguous. On the one hand the presence of large

[13] The following Nace Rev. 2 sectors have been classified by ISTAT as 'dynamic': CE-Chemicals; CF-Pharmaceuticals; CI-Computers and electronic and optical products; CJ-Electric apparatus; CL-Transport; M – Professional, scientific and technical activities; R – Arts, entertainment, recreation; S – Other service activities.

incumbent firms may hinder the entrepreneurial process, because of competition pressures (Aghion et al., 2006), and on the other large firms may be the source of spin-off firms. In order to control for this source of variance, we have included the ratio of public companies to the total registered firms in the region in the analysis as a proxy of the presence of large firms in the area.

Finally, in order to address the structural differences in institutions and culture among Italian regions (Quatraro, 2009b), we have also added regional dummy variables.

The variables used in our study are reported in Table 1 and their summary statistics are presented in Table 2.

>>> INSERT TABLES 1 AND 2 ABOUT HERE <<<

4.3 Methodology

The discrete and non-negative nature of the dependent variable suggests the adoption of estimation techniques for ‘count data’ models (Hausman et al., 1984).

As suggested by the summary statistics reported in Table 2, our dependent variable appears to be overdispersed, therefore the negative binomial estimator can be expected to perform better than the Poisson estimator (Greene, 2003).

The baseline specifications would consequently be the following:

$$NEWFIRM_{i,t} = \exp(\alpha + \beta_1 KSTOCK_{i,t-3} + \boldsymbol{Z}\gamma + \rho_i + \sum \psi t + \varepsilon_{i,t}) \quad (12a)$$

$$NEWFIRM_{i,t} = \exp(\alpha + \beta_2 COH_{i,t-3} + \beta_3 KV_{i,t-3} + \boldsymbol{Z}\gamma + \rho_i + \sum \psi t + \varepsilon_{i,t}) \quad (12b)$$

where *KSTOCK* is the stock of patents observed in the region, *COH* is the average degree of coherence amongst the technologies that feature the local knowledge base, and *KV* is the variety of combinations amongst the technologies that feature the local knowledge base. The error term is decomposed into ρ_i, which accounts for the fixed effects of the regions, the time dummies $\sum\psi t$ and the error component ε_{it}. It is worth noting that the variables that proxy the characteristics of the local knowledge base have been lagged three years in order to take account the amount of time required for them to translate into actual dynamics of new firm creation[14]. The correlation matrix is provided in Table 3.

>>> INSERT TABLE 3 ABOUT HERE <<<

It can be seen that KSTOCK is characterized by a high and significant correlation with the three measures of knowledge variety (KV, RKV, UKV). For this reason, we also checked the variance-inflation factor (VIF) for the covariates to detect any multicollinearity among them. A high value of VIF indicates the presence of multicollinearity. Neter et al. (1990) suggested 10 as a cut-off value for the VIF statistic. In our data, VIF was far lower than the threshold value in all of the tests. In particular, when KSTOCK was regressed on all the other covariates, including each of the three knowledge variety measures considered separately in different regressions, the VIF value assumed values in the 3.8-4.6 range, that is, much lower than the cut-off value of 10. Nonetheless, we ran different regression models. We first included the three specifications of knowledge variety (KV, UKV and RKV) in different regression models. We also ran different regression models in which the knowledge stock from the vector of covariates was excluded. The mean VIF is reported for each model at the bottom of the tables that present the results of the econometric results.

Vector ***Z*** includes the control variables discussed in section 3.2.3. All of these covariates, except the time-invariant ones, were lagged three years to minimize the risk of spurious relations.

4.3.1 Spatial Econometrics Methodologies

The geographical dimension of entrepreneurial dynamics mentioned in section 2 requires the possible effects of spatial dependence on the reliability of the results of the econometric estimation to be taken into account (Andersson, 2005; Plummer, 2010). When spatial dependence is at stake,

[14] While the 3-year lag is suitable from an economic viewpoint, it can also be justified by comparing the AIC and BIC of the same models run with different lag specifications.

traditional econometric models may yield biased results. In order to overcome this issue, a dedicated body of literature has proposed a number of estimators that are able to account for both spatial dependence among the relationships between observations, and spatial heterogeneity in the empirical model that has to be estimated. An early treatment of spatial econometric issues can be found in Anselin (1988), and this was subsequently extended by Le Sage (1999).

There are various ways of coping with this issue. First, it is possible to apply spatial filters to the sample data, to remove the spatial structure, and then apply traditional estimation techniques. Second, the relationship can be reframed using different kinds of panel data models: i) the spatial autoregressive model (SAR), which includes the spatially lagged dependent variable in the structural equation; ii) the spatial autocorrelation model (SAC), in which not only are the spatially lagged dependent variables included, in the right-hand-side of the equation, but the error term is also further decomposed to include a spatial autocorrelation coefficient; iii) the spatial Durbin model (SDM), which includes the spatial lag of one or more exogenous variables in the ***Z*** matrix of the covariates (Varga, 1998; Elhorst, 2003, 2010).

The nature of the dynamics under scrutiny makes the effects of knowledge spilling over from neighboring regions particularly relevant. In fact, interregional knowledge diffusion may provide local agents with additional entrepreneurial opportunities and may also affect the impact of knowledge variety and coherence on new firm formation. For this reason, SDM appears to be the most appropriate estimation model as it accounts for the effects of the spatial lag of both *KSTOCK* and the dependent variable. The choice of SDM is also supported also by Elhorst (2014), who showed that this estimator performs better than any other spatial econometric technique. It should be pointed out that the inclusion of the spatially lagged dependent variable allows the indirect effects that this variable may have on the dependent variables through the other regressors to be appreciated. In order to achieve a better understanding of the spatial dynamics, “a partial derivative interpretation of the impact from changes to the variables of different model specifications represents a more valid basis for testing this hypothesis" (Elhorst, 2014: 20). The main point is that "if a particular explanatory variable in a particular unit changes, not only will the dependent variable in that unit itself change, but also the dependent variables in other units. The first is called a direct effect and the second an indirect effect" (Elhorst, 2014: 21).

It should be noted that, in order to cope with the panel structure of the dataset, the implementation of the available spatial econometrics techniques calls for the transformation of our dependent variable to solve the problems, due to its non-negative and discrete nature[15]. According to Bonaccorsi et al. (2013), we used $\log\left[NEWFIRM_{i,t} + \left(NEWFIRM_{i,t} + 1\right)^{\frac{1}{2}}\right]$ as a dependent variable of the spatial econometrics estimations of the inverse hyperbolic sine transformation of the number of new firms. This transformation can be interpreted as a logarithmic transformation, which is preferred when the dependent variable assumes zero values for some observations. It also allows the influence of extreme observations to be mitigated (Johnson, 1949; Burbidge et al., 1988)[16].

5 Econometric results

The results of the negative binomial estimation are reported in Tables 4 and 5[17]. All the estimations include region and time fixed effects. It should be recalled that the dependent variable is only the

[15] The estimator proposed by Lambert et al. (2010) is not appropriate in the present context for two main reasons. First, it has been proven/used to work with cross sectional data, but this paper uses a panel of Italian provinces. Second, it proposes spatial count models based on a Poisson distribution, while our dependent variable is clearly overdispersed.
[16] This transformation is particularly useful when applied to dependent variables, since it reduces extreme values and renders the assumption of the normally distributed error terms on the right-hand-side reliable (MacKinnon and Magee, 1990).
[17] As a robustness check, we implemented regressions to control for the unemployment rate at the NUTS 3 level. Founding a new firm may be an alternative to uncertain future career prospects, or may represent "escape from unemployment" (see Oxenfeldt, 1943; Evans and Leighton, 1989; Storey, 1991, 1994). The empirical evidence that suggests the important role of job losses in fostering entry is quite robust (see Storey and Johnson, 1987; Santarelli et al., 2009; Audretsch and Vivarelli, 1995, 1996). Unfortunately, this variable is only available over a shorter time span. However, the results are consistent with those reported in the paper. A further check was made concerning the implementation of multi-level, mixed, fixed, negative, binomial estimation effects. This estimator is usually adopted when observations are organized at more than one level (e.g. NUTS2, NUTS1, etc…) (Goldstein, 1995). The results are in line with the evidence obtained from the negative binomial estimations and are available from the authors upon request.

count of new firms created in the MHT and HT sectors (see Appendix B for the sectoral correspondence), to minimize the risk of capturing entrepreneurs while neglecting sectors that, in principle, are less exposed to the effects of knowledge spillovers, such as agriculture and forestry, construction, etc.

Column (1) in Table 4 reports the results of the baseline model, which only takes into account the stock of knowledge due to the high correlation with the other knowledge-related variables. As expected, knowledge stock has a positive and significant effect on the creation of new firms at the local level. Therefore, the baseline model provides consistent results with the generic argument proposed by KSTE. This confirms Hypothesis 1 in this paper. If the control variables are considered, the proxy for agglomeration economies, POP_DENS, shows a positive and significant coefficient, as expected. The clustering of people in the area represents a source of competitiveness for prospective entrepreneurs. The FIRM_DENS variable has a positive and significant coefficient. The agglomeration of incumbent firms in the same sectors is a source of valuable knowledge spillovers. The presence of incubators (INC) in the region has the expected positive (and significant) coefficient. The employment level in manufacturing sectors (MANEMP) also has a positive and significant coefficient, in line with the 'labor market' approach to new firm creation. The share of public companies (PUB_COMP) is characterized by a negative but significant coefficient, thus supporting the idea that the presence of large incumbents represents a threat to prospective entrepreneurs. OPENNESS also yields a positive and significant coefficient, in line with the established literature. Finally, the quality of the local financial system and the distance from the region's main town do not seem to be significant.

>>> INSERT TABLE 4 ABOUT HERE <<<

The main hypothesis in this work is that since knowledge is a type of heterogeneous goods, it is necessary to investigate the specific features of the local knowledge bases that might favor or hinder the creation of new firms. For this reason, we exploited the information contained in patent data to calculate the indicators that are discussed in detail in section 4.2.2.

Column (2) in Table 4 reports the results obtained after extending the baseline model to include the replacement of KSTOCK with KV, while, in column (3), KSTOCK is replaced by COH. Finally, column (4) reports the results from the model that included both COH and KV. The positive and significant coefficient of KV in columns (2) and (4) is consistent with the general argument proposed by evolutionary economists according to which higher levels of variety stimulate innovative dynamics and hence increase opportunities for knowledge-based entrepreneurship. This result therefore supports hypothesis 2.

The average coherence (COH) of the local knowledge base also shows a positive and significant coefficient in columns (3) and (4). This means that higher levels of new firm creation, in the MHT and HT sectors, can be observed in areas that feature knowledge bases which stem from the recombination of technologies whose average degree of relatedness is very high. This result confirms Hypothesis 3. The high degree of internal coherence of the regional knowledge base is associated with reduced knowledge asymmetries and uncertainty, as well as a consequent improvement in the entrepreneurial absorptive capacity. Prospective entrepreneurs are likely to possess knowledge backgrounds and competences that are highly complementary to the knowledge generated in the area and which has remained unexploited. In this situation, they are better able to correctly screen, monitor and evaluate entrepreneurial opportunities from knowledge spillovers.

The coefficients of the other control variables show consistent signs and significance levels with the estimations of the baseline model reported in column (1).

In columns (1) and (2) in Table 5, KV has been replaced with RKV and UKV, respectively. Column (3) presents the results of the estimations in which RKV and UKV are both included in the model. The coefficients of both variables are positive and significant across the three columns. It should be recalled that related and unrelated knowledge variety measures are not opposites, but are instead orthogonal in meaning (Frenken et al., 2007; Castaldi et al., 2015). In principle, a NUTS 3 region can be characterized by both high RKV and high UKV. These would be/This would be the case of regions that are diversified across different macro technological fields, but are also diversified into many specific classes within each of these categories. It should be pointed out that empirically related variety and unrelated variety tend to correlate positively (see Table 3; see also Frenken et al., 2007; Quatraro, 2010,; Boschma et al., 2012; Hartog et al., 2012). Thus, the present results suggest that increased variety, in terms of both observed technological domains and technological classes within domains, is associated with higher levels of new firm creation. The signs and coefficients of the control variables are consistent with those observed for the baseline model.

>>> INSERT TABLE 5 ABOUT HERE <<<

Table 6 shows the results obtained after running the regressions that included KSTOCK as a regressor along with COH, KV, RKV and UKV. It should be noted that variety, whether unrelated (UKV) or related (RKV), as well as COH show quite robust coefficients, while the significance level of KSTOCK appears less stable. Finally, and more importantly, the calculation of the margins at means for the RKV and UKV has revealed that the former yields a stronger effect than the latter. For example, if the margins are computed drawing on the coefficients reported in columns (6) and (8), the margin of RKV is 0.255, and that of UKV is 0.178. These results, along with the positive coefficient of COH obtained in the previous regressions, provide further support of hypothesis 3.

>>> INSERT TABLE 6 ABOUT HERE <<<

The evidence discussed so far suggests an interesting picture of the kind of knowledge that is conducive to higher levels of entrepreneurial dynamics in the MHT and HT sectors. The interpretation of the effects of the knowledge indicators, based on previous evidence from different empirical contexts, suggests that the ‘rich integration’ regional knowledge production mode is more suitable to trigger the creation of new ventures based on the commercial exploitation of local knowledge that has been left unused by incumbents. Entrepreneurial absorptive capacity is favoured by the accumulation of highly integrated and complementary technological competences in the region.

However, as observed in section 3, the geographic dimension of entrepreneurial dynamics calls for a proper accounting of the spatial dependence in the econometric estimation. This issue is addressed in the next section.

5.1 Spatial Econometrics Analysis

A check on the robustness of our results for spatial dependence has been carried out by implementing spatial econometrics techniques. The estimation of spatial econometrics models was implemented using the STATA 12 software and running the XSMLE command, which allows for the maximum likelihood estimation of spatial panel data models (Belotti et al., 2013).

According to Elhorst (2014), we implemented an SDM in an attempt to understand the effects of the spatial lag of KSTOCK and the dependent variable. All the estimations included region and time fixed effects. We used a row normalized distance weighting matrix, obtained from latitude and longitude coordinates, for the regions and the STATA command SPMAT. The results are reported in Table 7.

>>> INSERT TABLE 7 ABOUT HERE <<<

Table 7 reports the coefficients of the estimations. The signs and significance of the control variables are consistent with the previous estimations. When we look at the relevant variables, KSTOCK shows a positive and significant coefficient, thus providing further support of the baseline hypothesis derived from KSTE. When we consider the characteristics of the local knowledge bases, both KV and the UKV and RKV components show positive and significant coefficients, thus supporting the hypothesis that the structure of knowledge matters. However, the support we have found so far is only partial, since COH has a positive but non-significant coefficient.

The evidence on the spatially lagged variables shows that both KSTOCK and the transformation of NEWFIRM yield negative and significant coefficients. However, it should be recalled that we used an inverse distance matrix. The negative coefficients imply that any increase in these variables in neighboring regions will have negative effects on new firm formation in the focal region. This can be interpreted as an effect of competition dynamics, according to which the higher the knowledge stock in neighboring regions, and therefore the higher the entrepreneurial opportunities therein, the more the prospective entrepreneur in a given region will be discouraged from pursing the entrepreneurial idea.

However, we have noted that Pace and Le Sage (2009) suggested going beyond the coefficients that result from the estimation and implementing a partial derivative approach, to fully appreciate the effects of the spatial dynamics. For this reason, we have reported the direct and indirect effects of the relevant variables in Table 8.

>>>INSERT TABLE 8 ABOUT HERE <<<

If we focus on the direct effects, i.e. the intraregional impact of the explanatory variables, it is possible to observe that the direct effect of KSTOCK is positive and significant, thus providing support of the basic hypothesis that the local availability of knowledge enhances the creation of new firms in the MHT and HT sectors. The COH and KV coefficients are positive and significant, and this also applies to RKV and UKV. The variety of combinatorial patterns amongst/among/of the different technologies in the region positively affects the emergence of new entrepreneurial opportunities.

If we move on to indirect effects, it seems that the negative effects of spatially lagged variables do in fact affect the way a knowledge structure shapes entrepreneurial dynamics. It would seem that the emergence of entrepreneurial opportunities in the MHT and HT sectors in neighboring locations reduces the opportunities of prospective entrepreneurs in the same sectors in a given region because of competition dynamics. It should be noted that the indirect effect of COH is not statistically significant.

Overall, the check on spatial dependence suggests that both entrepreneurial dynamics and the knowledge produced in neighboring regions matter for the creation of new firms in the MHT and HT sectors. However, the direct effects of the knowledge-related variables do not seem to be affected, while the indirect effects are shaped by competition over limited entrepreneurial opportunities from prospective neighboring entrepreneurs.

6 Discussion and Conclusions

The dynamics of new firm creation have received increasing attention in recent years, starting from the Schumpeterian notion of the entrepreneur as an agent of change and an engine of economic growth. The literature on the topic is extensive, ranging from micro-level analyses that focus on the idiosyncratic features of entrepreneurs running new firms, to macro-level analyses focused on the relationship between the features of the local economy and new firm formation.

This paper contributes to the latter strand of analysis by investigating how the structure of local knowledge bases affects new firm creation dynamics. To this end, we have combined an extended version of KSTE, stressing the importance of the knowledge filter and entrepreneurial absorptive capacity, with the recombinant knowledge approach. This has allowed us to elaborate a taxonomy of the modes of regional knowledge production based on two dimensions, i.e. technological relatedness and variety, to show that knowledge spillovers are important from a quantitative viewpoint, and that the nature of knowledge also matters.

The results of the empirical analysis are in line with the results found in the KSTE literature, which are synthesized in Hypothesis 1, according to which the greater the pool of knowledge available in the local context, the higher the rate of creation of new firms (Acs et al., 2009; Bonaccorsi et al., 2013; Audrestch and Lemann, 2005). Moreover, according to hypotheses 2 and 3, the effects of the configuration of the local knowledge bases are robust across different specifications as are the checks for spatial dependence, and have allowed us to further qualify the arguments in the KSTE literature.

The evidence concerning the formation of new high-technology and medium-high-technology firms in Italian provinces suggests that the availability of local knowledge spillovers is not sufficient per se to lead to the creation of new firms. The 'size' effect is important in that the knowledge generated in a given context by 'knowledge incubators', i.e. firms, universities and research laboratories, is a key source of entrepreneurial opportunities, provided it has remained unexploited by incumbents.

However, the structure of the local knowledge stock is just as important in identifying the conditions that favor knowledge-driven entrepreneurial dynamics. KSTE in fact considers entrepreneurs as agents that are able to fill the gap between the production of new ideas and their commercialization. The knowledge filter creates this gap, which is a consequence of the basic features of knowledge as a type of economic goods. These dimensions, and in particular uncertainty and asymmetries, can be affected by such characteristics as the average degree of relatedness and variety of the technological fields that feature the local knowledge base, and can exert an impact on how agents assess the expected value of knowledge-based entrepreneurial opportunities. Moreover, as synthesized in Figure 3, high levels of variety are associated with high levels of innovation, and hence of technological opportunities, while high levels of relatedness are associated with reduced knowledge asymmetries and uncertainty, as well as improvement in the entrepreneurial absorptive capacity of individuals in local contexts.

The evidence obtained on the basis of the knowledge indicators provides support to our hypotheses and shows that new firm formation is higher in contexts characterized by 'rich integration', i.e. high technological variety and high relatedness, as proxied by the RKV and COH indexes. On one hand, this could be due to the increased average ability of local prospective entrepreneurs to take advantage of knowledge that is close to their core technological competences accumulated over time. These dynamics draw upon a number of micro-level factors, related to the prospective entrepreneurs' absorptive capacity, accumulated competences and motivations, as well as to their capacity to establish network connections with agents active in different technological fields (Hayter, 2011; 2013; 2016).

On the other hand, our results are related to the basic dimensions of knowledge as a type of economic goods. Local knowledge bases, dominated by high levels of technological relatedness, are in fact characterized by lower degrees of asymmetry and lower levels of uncertainty related to the utilization of knowledge that has not been commercialized by incumbents. Again, the micro-foundations of aggregate level dynamics are based on the individual characteristics of prospective entrepreneurs, such as the degree of risk aversion and the scope of their competences.

Our results are also consistent with the literature that emphasizes the importance of relatedness in the regional branching process (Boschma, 2011; Boschma et al. 2013; Colombelli et al., 2014; Montresor and Quatraro, 2017).

This study introduces a number of policy implications. First, the promotion of knowledge-based entrepreneurship should be based on the combination and coordination of different sets of policies, i.e. entrepreneurship, technology and regional development policies. The policy mix should involve traditional entrepreneurship policies, based on a reduction in administrative and bureaucratic barriers to start new businesses, on easing access to financial programs, as well as on spreading entrepreneurship culture or mentoring programs (Storey 2003 and 2008). The set of policies aimed at enhancing the effectiveness of knowledge spillovers should instead involve actions such as the creation of science parks, incubators or technology transfer programs. These measures are aimed at reducing the filter, i.e. the barriers that prevent the exploitation of untapped knowledge by prospective entrepreneurs (Acs et al., 2003; Peters et al., 2004; Rice, 2002).

However, when knowledge-based entrepreneurship is at stake, our results suggest that regional development and technology policies may shape the dynamics by promoting research and innovation activities that valorize the technological competences accumulated over time. By setting a direction for technological efforts, local policymakers should stimulate the enrichment of the portfolio of place-specific competences, through entry into new and related domains. Knowledge-based entrepreneurship policies are likely to be more effective in contexts in which the plans for the evolution of regional technological trajectories are based on the careful assessment of the core competitive technological advantage of places and of the related technological opportunities. Targeted public procurement or R&D funding in specific technological fields can represent viable instruments in this respect.

The complementarity between entrepreneurship and regional technology policies is consistent with the regional branching argument, and represents a useful input for the latest wave of European regional policies based on the concept of smart specialisation strategies (S3) (Boschma 2014; Boschma and Giannelle 2014; Montresor and Quatraro, 2017; Capello, 2014; Camagni and Capello, 2013; Foray et al., 2011; OECD, 2013). McCann and Ortega-Argiles (2011) stressed that the geographical dimension of S3 is related to the effects of regional features on entrepreneurs' abilities to engage in successful learning processes. Entrepreneurship policies within the S3 policy framework should enhance the entrepreneurial search and discovery of what a region is best at doing, in terms of R&D and innovation, by applying them to its existing specialization patterns (Foray, David, and Hall 2009).

Overall, this study represents an important step forward in the understanding of the mechanisms behind knowledge-based entrepreneurship, with respect to the role of place-specific technological specializations. The proposed framework opens up an avenue for future studies that could investigate the geography of the modes of regional knowledge production, by mapping territorial units onto the taxonomy shown in Figure 3. It could be just as interesting to investigate the changing geography of the modes of knowledge production, to visualize whether and how regions move from one quadrant in another one in the same Figure, and to understand the determinants and effects of differential configurations of the knowledge base, as well as of movements over time.

Another relevant application of the proposed framework concerns the investigation of the relationship between the configurations of regional knowledge bases and the patterns of entrepreneurship-based dynamics of regional technological and economic diversification. For example, ‘rich integration’ could be expected to be associated with diversification in the related economic or technological fields, while ‘rich dispersion’ could be expected to drive the entry into fields that are loosely related to established local capabilities. In this framework, it could also be interesting to ascertain how the presence of foreign-born entrepreneurs or multi-national corporations in the region moderates the effects of the modes of knowledge production on regional diversification patterns.

Moreover, local contexts shape the dynamics of a firm. In this direction, the proposed taxonomy may help shed new light on the interplay between local knowledge spillovers and the innovation performances of firms. Future studies could attempt to link the modes of regional knowledge production to the rate and direction of technological change in firms, as well as to the quality of their innovation outputs, or to efforts aimed at generating incremental vis-à-vis radical innovations.

7 References

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Table 1 - Description of the variables used in the analysis

Variable	Description	SOURCE
NEWFIRMS	count of the new firms in medium-high technology and high-technology sectors (see appendix B) in each province at time t	MOVIMPRESE
FIRM_DENS	logarithm of the ratio between the number of registered firms in medium-high technology and high-technology sectors at time *t* in region *i* and the land use area	MOVIMPRESE
POP_DENS	logarithm of the ratio between the population and the land use area of region i at time t	CAMBRIDGE ECONOMETRIC S
KSTOCK	logarithm of the regional knowledge stock of region i	OECD REGPAT DATABASE
COH	logarithm of the average knowledge coherence of a region's knowledge base at time t	
KV	logarithm of the knowledge variety of region i at time t	OECD REGPAT DATABASE
RKV	logarithm of the related knowledge variety of region i at time t	OECD REGPAT DATABASE
UKV	logarithm of the unrelated knowledge variety of region i at time t	OECD REGPAT DATABASE
CD	logarithm of the average cognitive distance of a region's knowledge base at time t	OECD REGPAT DATABASE
IND_DIV	Herfindal-Hirschman index of the shares of incumbent firms in each industry at time *t* in region *i* (2-digits)	MOVIMPRESE
INC	Logarithm of the number of incubators in region i at time t	
MANEMPL	Logarithm of the employment level in the manufacturing sector of region i at time t	ISTAT
OPENNESS	Ratio between exports in the global dynamic-demand sectors and total exports	ISTAT
FIN_SYSTE M	Capital decay rate	ISTAT
PUB_COMP	Share of public companies in the region	MOVIMPRESE

Table 2- Descriptive Statistics

variable	N	mean	min	max	sd	skewness	kurtosis
NEWFIRMS	920	75.542	4.000	629.000	78.452	3.706	20.839
POP_DENS	920	5.156	3.619	7.886	0.737	0.494	4.104
FIRM_DENS	920	0.539	0.073	2.104	0.382	5.395	5.395
IND_DIV	920	0.109	0.066	0.244	0.034	1.369	4.604
KSTOCK	920	0.521	0.000	1.630	0.361	0.607	2.667
COH	920	2.829	-0.194	4.401	0.247	-0.098	35.826
KV	920	1.431	0.000	2.310	0.635	-1.249	3.527
RKV	920	1.099	0.000	2.053	0.586	-0.800	2.490
UKV	920	0.814	0.000	1.340	0.398	-1.174	3.066
INC	920	0.600	0.000	2.079	0.584	0.472	2.150
DIST	920	3.412	0.000	5.057	1.748	-1.306	3.002
MANEMPL	920	3.339	0.993	5.722	0.912	-0.009	2.698
OPENNESS	920	3.192	0.232	4.548	0.732	3.139	3.139
FIN_SYSTEM	920	0.985	0.152	3.262	0.475	4.913	4.913
PUB_COMP	920	0.121	0.040	0.324	0.044	5.410	5.410

Table 3 - Pairwise Correlation Coefficients

	NEWFIRMS	POP_DENS	FIRM_DENS	IND_DIV	KSTOCK	COH	KV	RKV	UKV	INC	DIST	MANEMPL	OPENNESS	FIN_SYSTEM	PUB_COMP
NEWFIRMS	1,000														
POP_DENS	**0,442**	**1,000**													
FIRM_DENS	**0,480**	**0,901**	1,000												
IND_DIV	**-0,254**	**-0,416**	**-0,530**	1,000											
KSTOCK	**0,245**	**0,231**	**0,410**	**-0,524**	1,000										
COH	**0,050**	**0,001**	**-0,012**	**-0,099**	**0,190**	1,000									
KV	**0,327**	**0,429**	**0,491**	**-0,538**	**0,716**	**0,212**	1,000								
RKV	**0,342**	**0,435**	**0,499**	**-0,476**	**0,744**	**0,211**	**0,945**	1,000							
UKV	**0,270**	**0,363**	**0,428**	**-0,544**	**0,600**	**0,123**	**0,873**	**0,691**	1,000						
INC	**0,270**	**0,173**	**0,238**	**-0,171**	**0,251**	**0,085**	**0,276**	**0,298**	**0,212**	1,000					
DIST	**-0,192**	**-0,235**	**-0,285**	**0,094**	-0,043	**-0,086**	**-0,130**	**-0,142**	**-0,121**	**-0,423**	1,000				
MANEMPL	**0,402**	**0,529**	**0,575**	**-0,452**	**0,609**	0,001	**0,682**	**0,678**	**0,621**	**0,358**	**-0,169**	1,000			
OPENNESS	**0,159**	**0,054**	**0,077**	**-0,065**	**0,131**	**0,107**	**0,156**	**0,178**	**0,113**	**0,200**	**-0,209**	**0,096**	1,000		
FIN_SYSTEM	**-0,110**	**-0,058**	**-0,234**	**0,358**	**-0,450**	**-0,019**	**-0,348**	**-0,326**	**-0,344**	**-0,129**	**0,035**	**-0,261**	**0,002**	1,000	
PUB_COMP	**0,218**	**0,594**	**0,707**	**-0,669**	**0,526**	**0,112**	**0,512**	**0,521**	**0,434**	**0,293**	**-0,202**	**0,506**	**0,072**	**-0,271**	1,000

Note: the correlation coefficients in bold are statistically significant

Table 4 – Fixed effect negative binomial estimations, baseline model

	(1) NEWFIRM	(3) NEWFIRM	(5) NEWFIRM	(7) NEWFIRM
KSTOCK	0.3846***			
	(0.1035)			
KV		0.2081***		0.1719***
		(0.0499)		(0.0517)
COH			0.2781***	0.2081***
			(0.0766)	(0.0791)
POP_DENS	0.3924***	0.2192**	0.3105***	0.2457**
	(0.1126)	(0.1106)	(0.1103)	(0.1109)
DIST	0.0080	0.0085	0.0190	0.0153
	(0.0168)	(0.0168)	(0.0169)	(0.0169)
FIRM_DENS	0.2563	0.4850**	0.4023**	0.5005**
	(0.1942)	(0.1962)	(0.1951)	(0.1956)
IND_DIV	-4.2679***	-4.0989***	-4.0798***	-4.0220***
	(1.0131)	(1.0111)	(1.0153)	(1.0083)
INC	0.2017***	0.1882***	0.2069***	0.1944***
	(0.0422)	(0.0425)	(0.0423)	(0.0423)
MANEMPL	0.2003***	0.2037***	0.2666***	0.2152***
	(0.0390)	(0.0379)	(0.0348)	(0.0380)
PUB_COMP	-10.3936***	-9.7238***	-9.8286***	-10.1554***
	(1.1246)	(1.0861)	(1.0933)	(1.0882)
FIN_SYSTEM	-0.0042	0.0044	0.0124	0.0115
	(0.0556)	(0.0554)	(0.0556)	(0.0554)
OPENNESS	0.0775**	0.0844***	0.0846***	0.0761**
	(0.0311)	(0.0307)	(0.0308)	(0.0308)
CONSTANT	3.1049***	3.6086***	2.4077***	2.9390***
	(0.5562)	(0.5630)	(0.5998)	(0.6153)
ALPHA	-1.2411***	-1.2446***	-1.2405***	-1.2522***
	(0.0469)	(0.0470)	(0.0469)	(0.0470)
N	910	910	910	910
pseudo R2	0.072	0.072	0.072	0.073
Mean VIF	5.7	5.6	5.3	5.2
AIC	9371.9239	9368.8440	9372.8002	9363.9929
BIC	9564.4617	9561.3818	9565.3380	9561.3441

All of the models include time and region fixed effects.
Standard errors in parentheses; all regressors are lagged three years
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5 – Fixed effects negative binomial estimations, Decomposing Knowledge Variety

	(1) NEWFIRM	(3) NEWFIRM	(5) NEWFIRM
RKV	0.2315***		0.2001***
	(0.0538)		(0.0569)
UKV		0.2165***	0.1245
		(0.0734)	(0.0770)
POP_DENS	0.2388**	0.2385**	0.2167**
	(0.1096)	(0.1114)	(0.1103)
DIST	0.0131	0.0057	0.0102
	(0.0168)	(0.0169)	(0.0168)
FIRM_DENS	0.4565**	0.4382**	0.4908**
	(0.1944)	(0.1973)	(0.1954)
IND_DIV	-4.5174***	-3.7918***	-4.2447***
	(1.0123)	(1.0260)	(1.0251)
INC	0.1932***	0.1914***	0.1886***
	(0.0424)	(0.0427)	(0.0424)
MANEMPL	0.2026***	0.2256***	0.1880***
	(0.0378)	(0.0375)	(0.0388)
PUB_COMP	-10.0408***	-9.0932***	-9.9108***
	(1.0959)	(1.0848)	(1.0969)
FIN_SYSTEM	0.0037	0.0053	0.0052
	(0.0556)	(0.0555)	(0.0554)
OPENNESS	0.0783**	0.0954***	0.0788**
	(0.0308)	(0.0306)	(0.0308)
CONSTANT	3.6812***	3.3969***	3.7193***
	(0.5625)	(0.5648)	(0.5630)
ALPHA	-1.2463***	-1.2352***	-1.2489***
	(0.0470)	(0.0469)	(0.0470)
N	910	910	910
pseudo R^2	0.073	0.072	0.073
Mean VIF	5.5	5.4	5.4
AIC	9367.5115	9377.1779	9366.9071
BIC	9560.0493	9569.7157	9564.2584

All of the models include time and region fixed effects.
Standard errors in parentheses; all regressors are lagged three years
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6 – Fixed effects negative binomial estimations, sensitivity analysis

	(1) NEWFIRM	(2) NEWFIRM	(3) NEWFIRM	(4) NEWFIRM	(5) NEWFIRM
KSTOCK	0.2930***	0.2643**	0.2254*	0.3502***	0.2314**
	(0.1094)	(0.1104)	(0.1168)	(0.1040)	(0.1167)
COH	0.2094**				
	(0.0825)				
KV		0.1608***			
		(0.0537)			
RKV			0.1748***		0.1411**
			(0.0611)		(0.0640)
UKV				0.1820**	0.1290*
				(0.0733)	(0.0767)
POP_DENS	0.3811***	0.3060***	0.3110***	0.3416***	0.2905**
	(0.1124)	(0.1156)	(0.1154)	(0.1141)	(0.1159)
DIST	0.0150	0.0075	0.0111	0.0047	0.0082
	(0.0170)	(0.0168)	(0.0168)	(0.0168)	(0.0169)
FIRM_DENS	0.3187	0.3882*	0.3752*	0.3350*	0.4082**
	(0.1953)	(0.1984)	(0.1977)	(0.1964)	(0.1985)
IND_DIV	-4.1637***	-4.1787***	-4.4877***	-3.9323***	-4.2063***
	(1.0108)	(1.0078)	(1.0102)	(1.0187)	(1.0226)
INC	0.2053***	0.1911***	0.1950***	0.1932***	0.1903***
	(0.0421)	(0.0423)	(0.0422)	(0.0423)	(0.0423)
MANEMPL	0.2166***	0.1724***	0.1794***	0.1719***	0.1634***
	(0.0394)	(0.0401)	(0.0396)	(0.0406)	(0.0407)
PUB_COMP	-10.6262***	-10.4657***	-10.5632***	-10.2788***	-10.4465***
	(1.1210)	(1.1180)	(1.1203)	(1.1215)	(1.1206)
FIN_SYSTEM	0.0048	-0.0010	-0.0007	-0.0015	0.0006
	(0.0556)	(0.0554)	(0.0555)	(0.0554)	(0.0554)
OPENNESS	0.0723**	0.0730**	0.0707**	0.0763**	0.0712**
	(0.0310)	(0.0310)	(0.0310)	(0.0310)	(0.0310)
CONSTANT	2.5303***	3.4416***	3.5040***	3.2612***	3.5374***
	(0.5983)	(0.5637)	(0.5681)	(0.5588)	(0.5685)
ALPHA	-1.2481***	-1.2507***	-1.2502***	-1.2474***	-1.2530***
	(0.0470)	(0.0470)	(0.0470)	(0.0470)	(0.0470)
N	910	910	910	910	910
pseudo R^2	0.073	0.073	0.073	0.073	0.073
Mean VIF	5.3	5.7	5.7	5.5	5.6
AIC	9367.6290	9365.1061	9365.7833	9367.8286	9364.9654
BIC	9564.9802	9562.4573	9563.1345	9565.1798	9567.1301

All of the models include time and region fixed effects.
Standard errors in parentheses; all regressors are lagged three years
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7 - Spatial Econometrics Estimations

	(1) NEWFIRM	(2) NEWFIRM	(3) NEWFIRM	(4) NEWFIRM	(5) NEWFIRM
KSTOCK	0.5145***				
	(0.0852)				

KV		0.2904***			
		(0.0452)			
RKV			0.2910***		
			(0.0475)		
UKV				0.3843***	
				(0.0665)	
COH					0.1298
					(0.0815)
POP_DENS	0.5354***	0.3346***	0.3526***	0.3654***	0.4814***
	(0.0978)	(0.0999)	(0.0997)	(0.0997)	(0.0991)
FIRM_DENS	0.3026	0.5540***	0.5163***	0.5115***	0.3458*
	(0.1861)	(0.1890)	(0.1886)	(0.1892)	(0.1896)
IND_DIV	-4.9960***	-4.4141***	-5.0342***	-3.8980***	-4.7013***
	(0.9371)	(0.9368)	(0.9370)	(0.9519)	(0.9560)
INC	0.1272***	0.1234***	0.1291***	0.1249***	0.1573***
	(0.0396)	(0.0396)	(0.0396)	(0.0398)	(0.0403)
PUB_COMP	-11.2059***	-10.2995***	-10.5560***	-9.4700***	-9.1402***
	(1.0268)	(0.9779)	(0.9918)	(0.9637)	(0.9809)
FIN_SYSTEM	0.0220	0.0373	0.0299	0.0420	0.0298
	(0.0530)	(0.0529)	(0.0530)	(0.0532)	(0.0540)
OPENNESS	0.0520*	0.0534*	0.0482*	0.0642**	0.0706**
	(0.0285)	(0.0284)	(0.0286)	(0.0284)	(0.0289)
Wx					
L3_kstock	-1.2807***	-1.2451***	-1.1986***	-1.3554***	-1.2463***
	(0.1754)	(0.1752)	(0.1760)	(0.1761)	(0.1813)
Spatial					
rho	-0.2289***	-0.2127***	-0.2215***	-0.2091***	-0.2312***
	(0.0596)	(0.0596)	(0.0596)	(0.0598)	(0.0602)
Variance					
sigma2_e	0.2898***	0.2887***	0.2897***	0.2912***	0.3004***
	(0.0136)	(0.0135)	(0.0136)	(0.0136)	(0.0141)

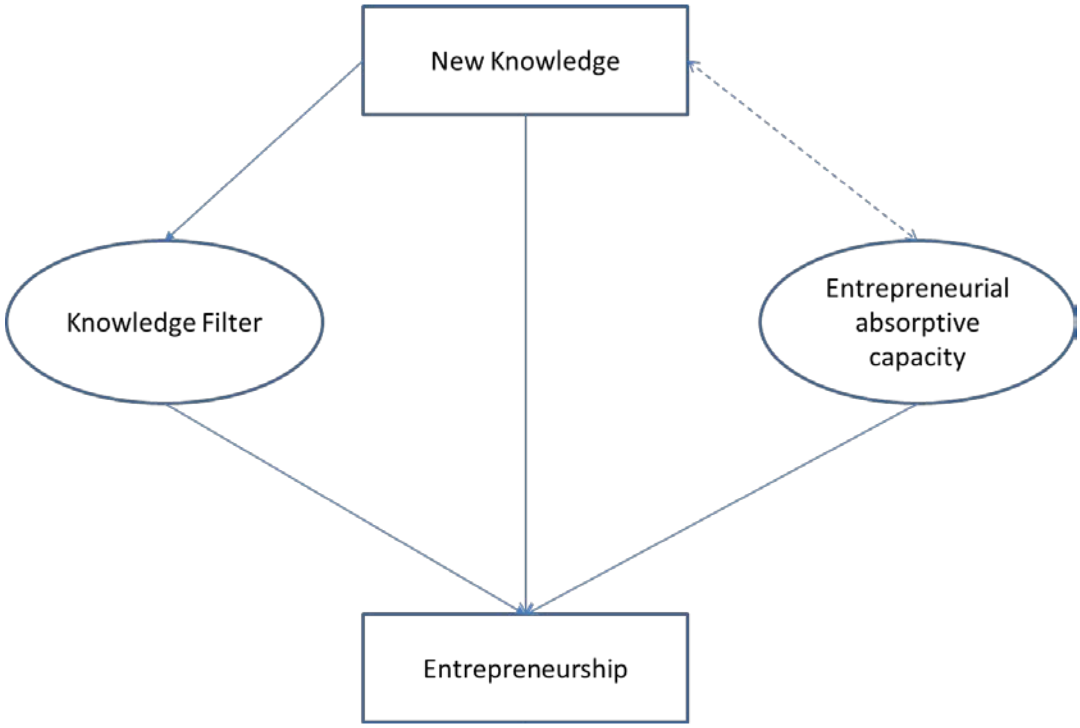
All of the models include time and region fixed effects.
Standard errors in parentheses; all regressors are lagged three years
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8 – Direct, indirect and total effects of the relevant variables after spatial econometrics estimation

Direct effects					
KSTOCK	0.5693***	0.0435***	0.0436***	0.0465***	0.0473***
	(0.0820)	(0.0128)	(0.0124)	(0.0137)	(0.0131)
KV		0.2942***			
		(0.0424)			
RKV			0.2950***		
			(0.0447)		
UKV				0.3893***	
				(0.0624)	
COH					0.1332*
					(0.0768)
Indirect effects					
KSTOCK	-1.2101***	-1.0902***	-1.0449***	-1.1887***	-1.0796***
	(0.1438)	(0.1522)	(0.1504)	(0.1555)	(0.1538)
KV		-0.0524***			
		(0.0152)			
RKV			-0.0545***		
			(0.0157)		
UKV				-0.0682***	
				(0.0206)	
COH					-0.0255
					(0.0162)
N	920	920	920	920	920
AIC	1715.4479	1716.8152	1720.4399	1724.4308	1754.7341
BIC	2284.7240	2300.5645	2304.1891	2308.1800	2338.4833

All of the models include time and region fixed effects.
Standard errors in parentheses; all regressors are lagged three years
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 1



Source: authors' elaboration on Qian and Acs (2013).

Figure 2

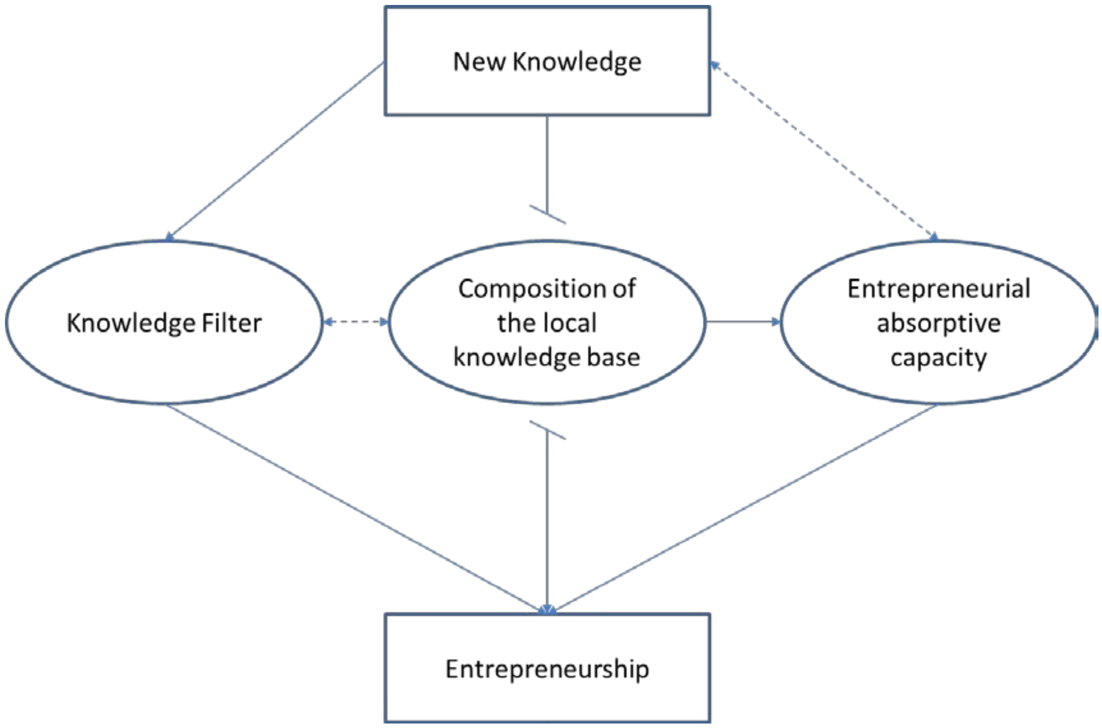


Figure 3

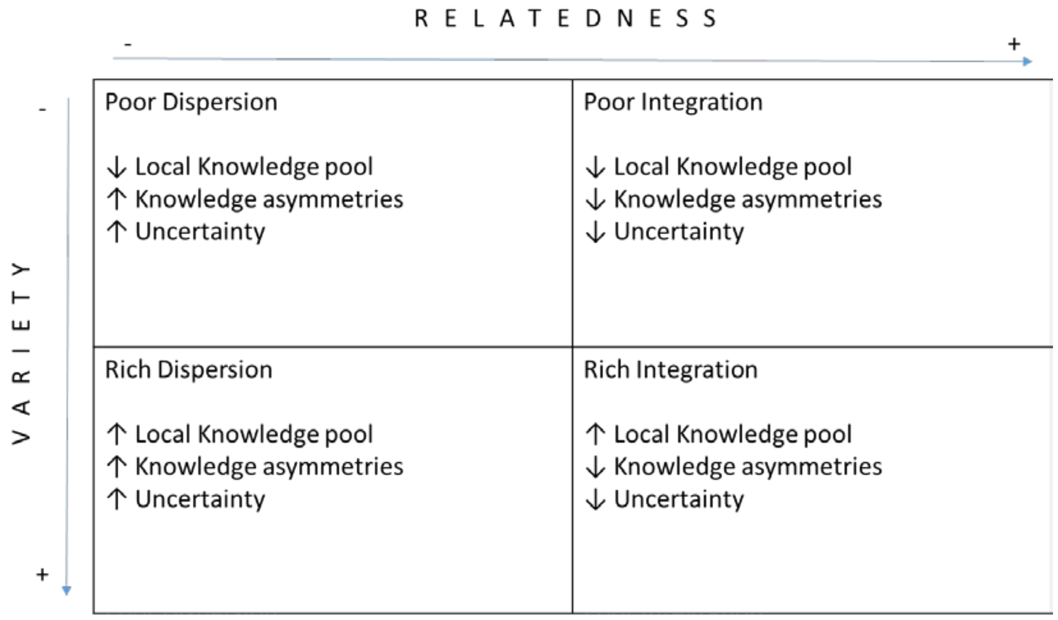
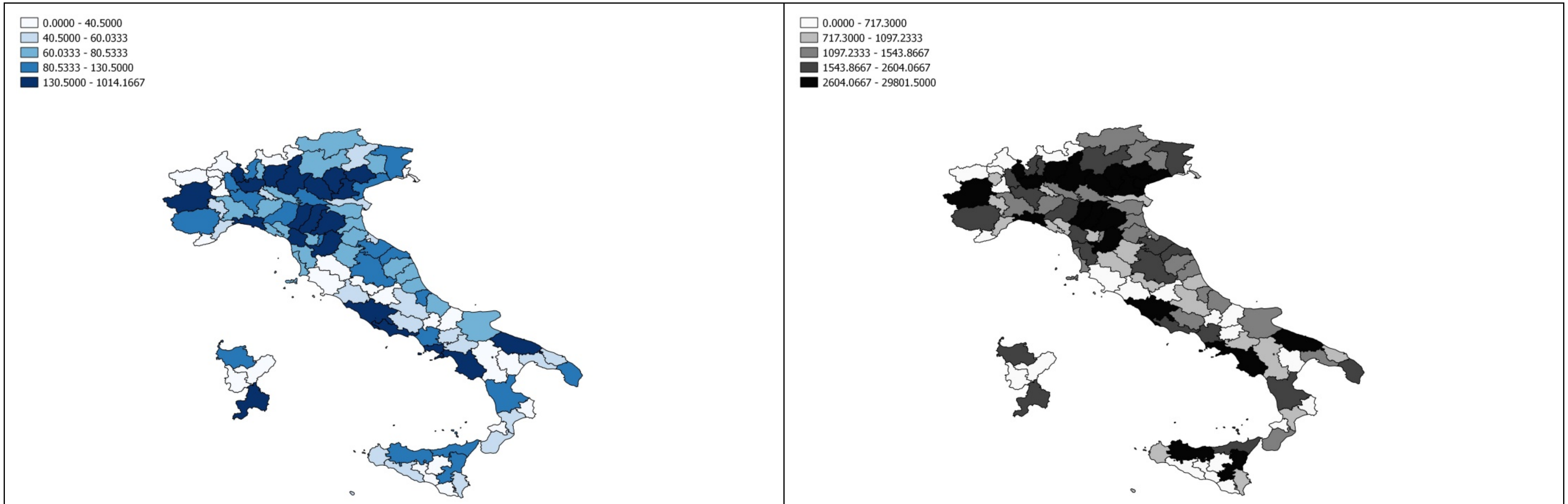

RELATEDNESS
-
+
VARIETY
-
+
Poor Dispersion
↓ Local Knowledge pool
↑ Knowledge asymmetries
↑ Uncertainty
Poor Integration
↓ Local Knowledge pool
↓ Knowledge asymmetries
↓ Uncertainty
Rich Dispersion
↑ Local Knowledge pool
↑ Knowledge asymmetries
↑ Uncertainty
Rich Integration
↑ Local Knowledge pool
↓ Knowledge asymmetries
↓ Uncertainty

Figure 4 – Newborn firms and stock of firms in medium-high and high technology sectors (average values 2001-2006)



a) Newborn firms in medium-high and high technology sectors

b) Stock of firms in medium-high and high technology sectors

APPENDIX A – Calculating Technological Relatedness τ[18]

Section 4.2.2 described how the knowledge coherence index, at the level of the generic region *i*, was derived. Here, we describe the steps needed to set the τ parameter, i.e. *technological relatedness*. First, we built a relatedness matrix as follows (Nesta, 2008). Let the technological universe consist of *k* patent applications. Let $P_{jk} = 1$, if the patent *k* is assigned to technology *j* [j = 1, …, n], and 0 otherwise. The total number of patents assigned to technology *j* is $O_j = \sum_k P_{jk}$. Similarly, the total number of patents assigned to technology *m* is $O_m = \sum_k P_{mk}$. Since two technologies may be present within the same patent, $O_j \cap O_m \neq \varnothing$, the number of observed co-occurrences of technologies *j* and *m* is $J_{jm} = \sum_k P_{jk} P_{mk}$. By applying this relationship to all the possible pairs, we obtain a square matrix Ω (n × n) where the generic cell is the observed number of co-occurrences:

$$\Omega = \begin{bmatrix} J_{11} & & J_{j1} & & J_{n1} \\ \vdots & \ddots & & & \vdots \\ J_{1m} & & J_{jm} & & J_{nm} \\ \vdots & & & \ddots & \vdots \\ J_{1n} & \cdots & J_{jn} & \cdots & J_{nn} \end{bmatrix} \tag{A1}$$

We can assume that the number x_{jm} of patents assigned to both the *j* and *m* technologies is a hypergeometric random mean and variance variable:

$$\mu_{jm} = E(X_{jm} = x) = \frac{O_j O_m}{K} \tag{A2}$$

$$\sigma^2_{jm} = \mu_{jm}\left(\frac{K - O_j}{K}\right)\left(\frac{K - O_m}{K - 1}\right) \tag{A3}$$

If the observed number of co-occurrences J_{jm} is larger than the expected number of random co-occurrences μ_{jm}, then the two technologies are closely related: the fact that the two technologies

[18] This appendix builds on Quatraro (2010, 2014).

occur together in the number of patents x_{jm} is not random. Thus, the measure of relatedness is given by the difference between the observed and the expected number of co-occurrences, weighted by their standard deviation:

$$\tau_{jm} = \frac{J_{jm} - \mu_{jm}}{\sigma_{jm}} \qquad \text{(A4)}$$

It should be noted that this measure of relatedness has lower and upper bounds: $\tau_{jm} \in \left]-\infty;+\infty\right[$. Moreover, the index shows a similar distribution to a t-student distribution; so, if $\tau_{jm} \in \left]-1.96;+1.96\right[$, one can safely assume the null hypothesis of non-relatedness of the j and m technologies. Therefore, the technological relatedness matrix **Ω**' can be considered a weighting scheme to evaluate the technological portfolio of regions.

APPENDIX B – List of sectors classified as medium-high and high-technologies

NACE Rev 1.1	Definition	Class
24.4	Manufactures of pharmaceuticals, medicinal chemicals and botanical products	HT
30.0	Manufactures of office machinery and computers	HT
32.1	Manufactures of electronic valves, tubes and other electronic components	HT
32.2	Manufactures of television and radio transmitters and apparatus for line telephony and line telegraphy	HT
32.3	Manufacture of television and radio receivers, sound or video recording or reproducing apparatus and associated goods	HT
33.1	Manufacture of medical and surgical equipment and orthopaedic appliances	HT
33.2	Manufacture of instruments and appliances for measuring, checking, testing, navigating and other purposes, except industrial process control equipment	HT
33.3	Manufacture of industrial process control equipment	HT
33.4	Manufacture of optical instruments and photographic equipment	HT
33.5	Manufacture of watches and clocks	HT
35.3	Manufacture of aircraft and spacecraft	HT
24.1	Manufacture of basic chemicals	MHT
24.2	Manufacture of pesticides and other agro-chemical products	MHT
24.3	Manufacture of paints, varnishes and similar coatings, printing ink and mastics	MHT
24.5	Manufacture of soap and detergents, cleaning and polishing preparations, perfumes and toilet preparations	MHT
24.6	Manufacture of other chemical products	MHT
24.7	Manufacture of man-made fibres	MHT
29.1	Manufacture of machinery for the production and use of mechanical power, except aircraft, vehicle and cycle engines	MHT
31.1	Manufacture of electric motors, generators and transformers	MHT
31.2	Manufacture of electricity distribution and control apparatus	MHT
31.3	Manufacture of insulated wire and cable	MHT
31.4	Manufacture of accumulators, primary cells and primary batteries	MHT
31.5	Manufacture of lighting equipment and electric lamps	MHT
31.6	Manufacture of electrical equipment n.e.c.	MHT
35.2	Manufacture of railway and tramway locomotives and rolling stock	MHT
35.4	Manufacture of motorcycles and bicycles	MHT
35.5	Manufacture of other transport equipment n.e.c.	MHT