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ABSTRACT. There is wide consensus about the importance of green technologies in achieving superior economic and environmental performances. However, the literature on their determinants has neglected the creation of green start-ups as a way of introducing green technologies onto the market. Drawing upon the knowledge spillovers theory of entrepreneurship (KSTE) and on previous literature on the complex and systemic nature of green technologies, we have tested the relevance of local knowledge stocks, distinguishing between clean and dirty stocks, in the creation of green start-ups. Moreover, the effects of the technological composition of local stocks have been investigated, by focusing on both related and unrelated technological variety, as well as on coherence. Consistently with the recent literature, green start-ups are associated with higher levels of variety, thus pointing to the relevance of diverse and heterogeneous knowledge sources, although in related and complementary technological fields.

Keywords: Green start-ups; New Firm Formation; Energy-related technologies; Knowledge-Spillovers Theory of Entrepreneurship

JEL Classification Codes: L26, M13, R11, O33

1 Introduction

The economic analysis of environmental issues has received increasing attention over the last few decades. Within the wide body of literature on the subject, the dynamics pertaining to the creation of environmental innovations has recently become a key topic. Green technologies are currently regarded as a means of restoring the competitiveness of advanced countries, which has been harmed by the recent economic crisis (Gilli et al., 2014; Costantini et al., 2013; Cainelli et al., 2013; Ghisetti and Quatraro, 2013; Mazzanti and Zoboli, 2009). Their emergence is in fact believed to bring about new jobs and new perspectives for economic growth.

The implementation of empirical analyses on eco-innovation (EI) impacts and determinants has often been focused on the well-established patents-based measures, or on Community Innovation Surveys (CIS). These two approaches allow the generation and the adoption of EI to be appreciated, respectively. However, less attention has been dedicated to the main source of innovation that Schumpeter identified in his seminal 1912 book *The theory of Economic Development*, i.e. the entrepreneur. In this perspective, EI can be introduced in a specific context through the creation of new start-up firms involved in the generation and commercialization of technologies, in which the environmental performances of the firms that adopt them are improved.

This missing link is particularly problematic as there is increasing consensus on the key role of start-ups in the introduction of innovation and new technologies on the market, above all when radical technologies and their resulting contribution to economic growth are at stake (Aghion and Howitt, 1992; Wennekers and Thurik, 1999; Carree and Thurik, 2003; Audretsch et al., 2006). Moreover, the formation of new firms is a determinant of regional growth, cross-regional differences and regional employment dynamics (Fritsch and Schindele, 2011; Dejardin and Fritsch 2011). Therefore, understanding the dynamics of the creation of green start-ups can provide useful information on how to boost local development through the interaction of the positive effects of EIs and entrepreneurial dynamics.

This paper is aimed at filling this gap by linking the analysis of EIs, and in particular the literature on their complex and systemic nature, to the wide body of literature that has investigated the relationship between entrepreneurship and economic development at the regional level. In this stream of literature, starting from the observation that entrepreneurial activity is geographically clustered, both theoretical and empirical analyses have attempted to identify the characteristics and attributes of the local socio-economic systems that may have an impact on the formation of new firms (Fritsch, 1997; Reynolds et al., 1994; Carlton, 1983; Bartik, 1985; Audretsch and Fritsch, 1994; Feldman 2001; Lee et al. 2004; Colombelli, 2016; Quatraro and Vivarelli, 2015).

A recent strand of literature has pointed out the importance of local knowledge spillovers on the entrepreneurial process. A key reference in this domain is KSTE, conceptualized by Audretsch (1995) and then further developed by Audretsch and Lehmann (2005) and Acs et al. (2009), in which knowledge spillovers are linked to new-firm start-up activities.

The contribution of this paper to the extant literature is twofold. On the one hand, we extend the KSTE to the analysis of green start-ups, and we disentangle the differential impact of the 'clean' from the 'dirty' knowledge stock. On the other hand, we qualify the argument on the basis of which green technologies benefit from heterogeneous knowledge sources, by showing that the related variety and coherence play important roles.

Our analysis has focused on the patterns of new firm formation in Italian NUTS 3 regions (i.e. at the "province" level) by using the data on the creation of innovative start-ups in energy-related technologies (henceforth ERT) field, within the framework of the new regulations established through Law Decree no. 179, on 18 October, 2012.

This appears an appropriate context for this analysis for different reasons. First, the Italian economy appears to be stuck in mature industries and lagging behind, from a technological viewpoint, compared to other more advanced countries. Our investigation has allowed us to test the extent to which the relationship between the creation of innovative start-ups and technological knowledge is shaped by the regional technology context. Second, the Italian case has recently been the subject of increasing attention, due to both the availability of emission level data at the regional and sectoral levels, and to the marked regional heterogeneities in the attention to environmental performances (e.g. Costantini et al., 2013; Ghisetti and Quatraro, 2013 and 2017; Marin and Mazzanti, 2013; Mazzanti and Zoboli, 2009).

2 Theoretical framework

The literature on the determinants and effects of the formation of new firms has gained momentum over the last few decades (Vivarelli, 2013; Quatraro and Vivarelli, 2015). Of all the reasons behind such interest, the importance of entrepreneurs in the innovation process is undoubtedly the most relevant.

The academic and policy debate on the determinants and effects of innovation has recently begun to focus more and more on the capacity to reconcile economic and environmental performance through the generation, adoption and diffusion of green technologies. These are currently considered key factors in restoring the competitiveness of advanced countries that have been harmed by the economic crisis. Their emergence is in fact believed to create new jobs and introduce new perspectives for economic growth (Crespi et al., 2015). These arguments draw upon the so-called Porter hypothesis (Porter and van der Linde, 1995), according to which innovations aimed at improving the environmental performances of firms might also have positive effects on their economic performance, due to the enhancement of products and processes engendered by the adoption of the innovation.

Given the policy relevance of the phenomenon, which is based on the so-called double-externality problem, the prevalent interest in the analysis of the determinants of environmental innovation has concerned the extent to which environmental regulation may exert an incentive for firms to introduce innovations, for instance, to allow the polluting standards exogenously set by policymakers to be met. These studies adopt an induced innovation framework, in which stringent policy frameworks engender additional costs for firms, which in turn increase the total production costs by changing the relative factor prices. Firms adopt EIs to save on these costs, and in so doing they generate an increase in the derived demand for green technologies (Colombelli et al., 2015; Ghisetti and Quatraro, 2013; Brunnermeier and Cohen, 2003; Rennings and Rammer, 2011; Rennings and Rexhäuser, 2011; for a critical review of the empirical studies on this topic see del Rio, 2009 and del Rio et al., 2016). A different but related approach to the investigation of the endogenous factors that lead to the introduction of EIs can be found in the literature on corporate social responsibility (CSR) (Orlitzky et al. 2011; Hart, 1997).

The extant works on the determinants of green technologies stress the effects of environmental regulation on one hand, and their impact on the economic and financial performances of firms on the other (hand). A first systemic overview of this positive relationship was provided by Ambec and Lanoie (2008). Ghisetti and Rennings (2014) have recently extended the analysis framework by pointing out the importance of distinguishing between different kinds of EIs when studying their determinants and effects.

The empirical literature has mainly focused on green technologies, using either the Community Innovation Survey (CIS) or patent applications, which are considered ‘green’ according to international classification schemes, in particular in the WIPO Green Inventory, the OECD EnvTech and the ECLA Y02 class. Less attention has been devoted to the role of entrepreneurship as a driver of innovations in the realm of the environment (Meyskens and Carsrud, 2013; Cohen and Winn, 2007).

Entrepreneurs are currently considered the main agents of change, and in this respect, the establishment of new ventures is clearly an important channel through which new green technologies are generated on the market. Enquiring into the creation mechanisms of the new green start-ups therefore represents an additional, although till now less explored, avenue to help understand the determinants and effects of green technologies. The grafting of the analysis of the generation of EIs onto the KSTE could be far reaching, in that it would allow how the formation of green start-ups is connected to the features of the local contexts to be identified, both in terms of the availability of the local stock of knowledge, and in terms of scope and complementarity of the technological competences accumulated over time (Colombelli, 2016; Colombelli and Quatraro, 2013).

According to KSTE, new knowledge and ideas are main sources of entrepreneurial opportunities (Acs and Armington, 2006; Audretsch et al., 2006). In other words, new knowledge and ideas created in an incumbent organization, such as a firm or a university research laboratory, but which have not been commercialized, may serve as a source of entrepreneurial opportunities. KSTE therefore suggests that the start-up of a new firm is an endogenous response to opportunities that have been generated, but not fully exploited, by incumbent organizations.

In particular, KSTE proposes that some knowledge remains untapped, and could become available in local contexts because of its characteristics as economic goods (Arrow, 1962). In this context, 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). For these reasons, incumbent firms might decide not to follow up or commercialize new ideas that other individuals or groups might consider as potentially valuable (Audretsch et al., 2006). An important implication is that contexts characterized by greater amounts of knowledge generate more entrepreneurial opportunities (Audretsch and Keilbach 2007).

As far as green entrepreneurship is concerned, no systematic investigations have been found in the literature in which the phenomenon is connected to local knowledge spillovers. However, the literature on the knowledge sources for EIs can provide useful inputs to understand this link. One key finding, in this respect, concerns the complex and systemic nature of EIs, and the consequent need to access external knowledge sources for recombinant innovation processes (Florida, 1996; Oltra and Saint Jean, 2005a and b; Rennings and Rammer, 2009; Zeppini and van den Bergh, 2011; De Marchi, 2012; Cainelli et al., 2015). Rennings and Rammer (2009) and Horbach et al. (2013)

have suggested that the importance of external knowledge for EIs is due to the fact that firms, with the exception of firms in eco-industries, may require knowledge and competences that are not part of their core competences.

In this context, the basic mechanisms articulated by KSTE are expected to be all the more relevant for the formation of green innovative start-ups, due to the complex and systemic nature of their knowledge base. In view of the previous arguments, the following hypothesis can be advanced:

H1. *The amount of knowledge locally available is positively associated with the creation of 'green' innovative start-ups in a province.*

Although, in general, it could be expected that the formation of green start-ups is associated with the availability of local knowledge pools, an important refinement of the previous hypothesis should be introduced concerning the distinction between 'clean' and 'dirty' technologies. Dechezlepretre et al. (2014) compared knowledge spillovers from dirty and clean technologies, and found that clean technologies are cited more often than the dirty ones. They suggest that this evidence could be partially explained by the fact that GTs have more general applications, and they are radically new, compared to the more incremental dirty innovation. As far as the energy sector is concerned, Bjørner and Mackenhauer (2013) provided evidence on the effect of differential spillovers of private energy research institutions and compared it with the effects of non-energy private research institutions. Popp and Newell (2012) found that alternative energy patents are cited more frequently in the subsequent patents, and in a wider range of technologies, than other patents filed by the same firms. Clean technologies are therefore expected to yield more important effects on the generation of green innovative start-ups, because of their wider range of applications. Moreover, prospective entrepreneurs in the green domain are expected to have the necessary competences and absorptive capacity to master this kind of knowledge. These arguments led us to propose the following hypothesis.

H2. *Spillovers from clean technologies are expected to be stronger than spillovers from 'dirty' ones.*

Apart from the distinction between 'clean' and 'dirty' technologies, an important qualification of the dynamics at stake concerns the composition of the knowledge pools that are available at the local level. In most of the empirical literature pertaining to the KSTE approach, the local knowledge stock is actually proxied by R&D investments (Audretsch and Keilbach 2007; Acs et al. 2009) or by the research efforts carried out in co-localized universities and research centers

(Audretsch and Lehmann 2005; Cassia, Colombelli, Paleari 2009; Cassia and Colombelli 2008; Bonaccorsi et al. 2013; Bonaccorsi et al. 2014). However, these former studies neglected that not only does the size of the knowledge stock matter, but also its nature. In this context, the recent empirical analyses have focused on the effects of knowledge variety on the formation of new firms (Bae and Koo 2008; Bishop 2012; Colombelli and Quatraro 2013, Colombelli, 2016). These works can be considered as part of the literature that emphasizes that knowledge spillovers frequently occur across sectors (Jacobs' externalities). From this point of view, diversity in the local knowledge stock may have a positive impact on the generation of opportunities that entrepreneurs can exploit.

In view of the complex and systemic nature of EIs, Ghisetti et al. (2015) have shown that the breadth of the knowledge source, understood as diversity of knowledge sources, is a key determinant of successful adoption efforts. Rennings and Rammer (2009) also pointed out the relevance of diverse information sources. In the same direction, Horbach et al. (2013) introduced the hypothesis according to which EIs require more information sources. All these studies focused on the variety of typologies of actors a firm may interact with, in order to introduce EIs. However, a variety of actors also implies a variety of competences. Because of the recombinant and systemic nature of EIs, the availability of a variety of technological sources and domains provides a contextual feature that could be conducive to the successful exploitation of untapped knowledge. In view of the arguments developed above, the following hypothesis can be put forth:

H3. *The Knowledge Variety of the technological domains that feature a local knowledge base is positively associated with the creation of new green innovative start-ups in a province.*

When dealing with a variety of knowledge sources and technological domains, cognitive proximity (Boschma, 2005) can represent a crucial dimension that may affect the likelihood of success of entrepreneurial dynamics in green domains, as well as of achieving EIs in general (De Marchi, 2012). The concept of technological relatedness, and the distinction between related and unrelated variety can prove useful in this context (Frenken et al., 2007; Quatraro, 2010). In local contexts in which a high relatedness and a dominance of a related on unrelated variety are featured, cognitive distance is on overage reduced due to the high level of integration of the local knowledge base. This is expected to support the successful exploitation of technological opportunities by prospective entrepreneurs. The complex nature of the knowledge base that underpins the formation of green start-ups makes these dimensions particularly important for these dynamics.

H4. *The Related variety and the relatedness of knowledge sources are expected to be positively associated with the creation of green startups.*

3 The Italian Context

At the end of 2012, the Italian Ministry of Economic Development approved a Law Decree on “Further urgent measures for Italy’s economic growth”, in which specific measures aimed at promoting the creation and development of innovative start-ups were provided. This was the first time the Italian legislation had taken this kind of company into consideration. The law recognizes that start-ups are important for the promotion of sustainable growth, technological development and employment, in particular youth employment, and is aimed at developing an environment that will foster the creation of entrepreneurial opportunities, innovation and social mobility, will strengthen the links between universities and businesses, and will attract investments and talented people from abroad to Italy. At the end of 2014, more than 2000 innovative start-ups had registered at the Chambers of Commerce in Italy under this law.

In order to be included in the register of “innovative start-ups” and to benefit from governmental incentives, a new company needs to fulfill certain requirements. In particular, according to the Law Decree definition, a start-up is a corporation that is not listed or subject to Italian tax laws, which has a lower turnover than 5 million euros, has been operational for less than 48 months, is owned directly, for at least 51% by physical subjects, and, above all, has the social aim of developing innovative products or services, with a high technological content.

In order to satisfy this latter requirement and to be defined as innovative, a start-up needs to fulfill at least one of the following three criteria: either 15% of its costs are related to R&D activities, at least one third of the team is made up of highly qualified members, and, finally, the enterprise is the holder, depositary or licensee of a registered patent or the owner of an original registered computer program.

All the companies included in the register of “innovative start-ups” benefit from the support measures provided by the Law Decree, such as, the possibility of using the specific flexible employment contracts of start-ups of remunerating their team members and the providers of external services with stock options and work for equity, respectively, and of accessing incentives for the employment of highly qualified personnel. Moreover, the Law Decree also introduced a “fail fast” procedure, with the aim of offering the entrepreneurs the opportunity of starting a new business project as soon as possible.

In addition to the above, the Italian Government, in its attempt to stimulate entrepreneurial activities, provided some specific measures and incentives for incubators or accelerators that fulfil specific requirements concerning the physical structures, management, facilities and track record of the start-ups and which were also aimed at increasing the resources available for venture capital.

Given the particular features of the firms included in the Italian register of “innovative start-ups”, this appears an appropriate context in which to test the impact of knowledge spillovers on entrepreneurial activities in energy-related technologies.

4 Data, Methodology and Variables

4.1 Data

The studied sample includes 3712 innovative start-ups registered at the Chambers of Commerce in Italy. Our analysis was restricted to companies included in the “innovative start-ups” online directory that had registered at the Italian Chamber of Commerce between 2009 and 2015 in 103 Italian NUTS3 regions.

As knowledge spillovers are geographically bounded, it was necessary to focus on a sufficiently narrow definition of region. Therefore, the unit of analysis in this study was the NUTS 3 geographical area. The NUTS classification (Nomenclature of territorial units for statistics) is a hierarchical system that is used to divide up the economic territory of the EU. According to this nomenclature, EU countries are divided into geographical units at three levels of aggregation: NUTS 1, major socio-economic regions; NUTS 2, basic regions for the application of regional policies; NUTS 3, small regions for specific diagnoses. In Italy, NUTS 3 regions correspond to administrative units (provinces) that group together different neighboring municipalities. This administrative unit generally includes a city and its satellite municipalities. A NUTS 3 geographical area is characterized by the presence of frequent economic interactions. For example, almost every Italian NUTS 3 region has a Chamber of Commerce and a workers’ association. For this reason, this unit of analysis has been considered the most appropriate to define the regional boundary of entrepreneurial activities.

In order to analyze the impact of the structure of local knowledge bases on the formation of new firms, data on innovative start-ups, aggregated at the NUTS3 level of analysis, was matched with information contained in the OECD RegPat Database (February 2015), and also with data provided by the Italian institute of statistics (ISTAT), in particular the “Indicatori territoriali per le politiche di sviluppo” (local indicators for development policies).

The OECD RegPat is derived from the Patstat database, which guarantees worldwide coverage. These data pertain to both applications to the European Patent Office (EPO) and the application to the national patent offices, and it is possible to go back as far as 1920 for some patent authorities. This allows the traditional limitation of EPO based longitudinal analysis, due to its recentness, to be overcome.

Patent applications are regionalized at the NUTS 3 level on the basis of the inventors' addresses. Applications in which there are more than one inventor residing in different regions have been assigned to each of the regions according to the respective share. Our study has been limited to applications submitted by inventors residing in Italian regions, and has used the International Patent Classification (IPC) set up by the EPO to assign applications to technological classes.

The considered patents were then defined as being *environmental* on the basis of the World Intellectual Property Organization "WIPO IPC green inventory", an International Patent Classification that identifies patents related to the so-called "Environmentally Sound Technologies" and distributes them according to their technology fields, with the *caveat* that it is not the only possible classification of green technologies and which, like the other available classifications, presents some drawbacks (Costantini et al., 2013b)[1]. In line with the focus on the determinants of start-ups in ERT, we have focused on two subgroups of the WIPO Green Inventory, i.e. Energy Conservation and Alternative Energy Production (see the appendix for the correspondence with the IPC technological classes).

4.2 Variables

4.2.1 The dependent variable

The cumulative sum of the innovative start-ups registering for value added tax (VAT) in the NUTS3 region in energy-related technologies (ERT)[2] was taken into consideration to implement the empirical analysis. This appeared an appropriate context for the analysis for different reasons. First, it is expected that the role of knowledge spillover will be of particular importance in the creation of

[1] Although interesting, it is beyond the scope of the current work to systematically test for the differences that could arise from the choice of classification. (We selected t) The WIPO IPC green inventory was selected since it is currently a frequently used and well established classification of green technologies. OECD has also developed the OECD Indicator of Environmental Technologies (OECD, 2011), based on the International Patent Classification (IPC), which features seven environmental areas, i.e. (a) general environmental management, (b) energy generation from renewable and non-fossil sources, (c) combustion technologies with mitigation potential, (d) technologies specific to climate change mitigation, (e) technologies with potential or indirect contributions to emission mitigation, (f) emission abatement and fuel efficiency in transportation, and (g) energy efficiency in buildings and lighting. At the same time, the European Patent Office (EPO) is working on completing its own classification system (ECLA) to assign each patent a green tag, depending on the environmental aim of each patent. So far, EPO has allowed technologies to be tagged according to their adaptation or mitigation to climate changes (Y02), in terms of buildings (Y02B), energy (Y02E), transportation (Y02T) and the capturing, storage sequestration and disposal of GHG (Y02C). Costantini et al. (2013b) have recently pointed out the shortcomings of classification methods based on efforts to collect the IPCs that are potentially related to green technologies in one place. Focusing on the biofuel sector, they have shown that the WIPO Green Inventory is likely to overestimate the number of patents that have been assigned due to the fact that IPCs are not specifically designed to identify this narrow and very specific domain. Clinical analyses, based on a keyword search and validations by experts, are likely to yield finer grained classifications. Nonetheless, the WIPO Green Inventory was chosen for this work, due to the wide scope of this analysis, which encompasses many different kinds of green technologies.

[2] The Data are available to the public on the http://startup.registroimprese.it/ web-site. The data used in this paper were updated to May 2015.

innovative start-ups, which are mainly concentrated in the high-tech and knowledge intensive sectors. Second, the Italian economy appears to be stuck in mature industries, and significantly behind from a technological viewpoint, compared to other more advanced countries, and the investigation therefore allowed us to test the extent to which the relationship between the creation of innovative start-ups and technological knowledge is shaped by the regional technology context.

These data were provided by the Union of the Chambers of Commerce (Unioncamere) in the form of the Movimprese dataset. A company belongs to the ERT group if it exclusively develops and commercializes high-value innovative goods and services in the energy field.

It is worth noting that the extant literature has proposed two alternative approaches for the measurement of the formation of new firms, i.e. the ecological and the labour market approach. The ecological approach standardizes figures about new firm creation using the stock of existing firms, while the labour market approach uses the employment level. These approaches have been found to yield very different results when implemented in empirical settings characterized by the same exogenous variables (Audretsch and Fritsch, 1994).

Audretsch and Lehman (2005) and Bonaccorsi et al. (2013) have recently assumed that new firms in local contexts could be interpreted as count data. This approach has been followed here and the yearly count of the new ERT start-ups in each province ($ERT_{i,t}$) has been used as the dependent variable[3].

Figure 1 shows the distribution of both the total and ERT innovative start-ups across the Italian NUTS 3 regions over the entire observed period.

>>> INSERT FIGURE 1 ABOUT HERE <<<

The diagram shows that the overall number of innovative start-ups in the Italian regions over the observed period is nontrivial, although the figures about ERT innovative start-ups are not so impressive. This evidence is confirmed by the descriptive statistics in Table 2, according to which the maximum observed value for the variable is 16. The kernel density estimation of the variable distribution can be found in Annex 1. Overall, about 82% of the region-year observations take on a value 0 as far as the ERT is concerned. This is the reason why a zero-inflated negative binomial regression has been implemented, as will be explained in Section 4.3.

[3] However, we do not deny that local markets are not homogenous with respect to size, and that this can introduce some biases in our results. For this reason, as we specify below, we introduced the employment level in the province among the control variables.

4.2.2 Key explanatory variables

4.2.2.1 Knowledge Stock

The KSTE test involves the use of a measurement of the local knowledge stock. Either an input or an output measure can be used in this respect. The former would refer to local expenditure for research and development (R&D) as a proxy of the available pool of technological knowledge (Acs et al., 2009). Unfortunately, there are no available data concerning R&D expenditure at the NUTS 3 level in Italy. For this reason, an output measure was adopted, i.e. the local knowledge stock (KSTOCK), which is calculated by using patent applications and applying the permanent inventory method. To calculate the cumulated stock of previous patent applications, the initial observation is first set as follows:

$$KSTOCK_{i,t=0} = (1+\rho)/(\rho+\delta)*\dot{h}$$

It is worth noting that the first available information on Italian patents in the OECD RegPat database dates back to 1977. However, a good coverage of the data is ensured since 1985. Since the analysis of the determinants of green start-ups has focused on the 2009-2015 period, the use of the KSTOCK variable does not lead to any problems in terms of spurious results driven by the behaviour of regions toward the later periods. Moreover, as explained in section 4.3, by using lagged values of the explanatory variables, including KSTOCK, the results are not affected by truncation problems.

After having calculated the initial value of the KSTOCK for each region, the values of the subsequent years are obtained by applying the permanent inventory method using a rate of obsolescence of 15% per annum:

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

where $\dot{h}_{i,t}$ is the flow of patent applications and δ is the rate of obsolescence[4], where once again *i* is the region and *t* is the time period.

As anticipated in Section 4.1, in order to test H2, the stock of clean knowledge for each region has been built using the WIPO IPC Green Inventory, focusing on the Energy Conservation and Alternative Energy Production technological fields. (We labelled) This variable was labelled **GT_KSTOCK**.The complement variable **NOGT_KSTOCK** was then calculated as the stock of patents that are not associated with those two technological fields. Figure 2 shows the evolution of the three stock variables over time.

[4]A similar approach was used by Soete et Patel (1985).

>>> INSERT FIGURE 2 ABOUT HERE <<<

As far as the measurement of the characteristics of the local knowledge base is concerned, while some previous studies used sectoral data (Bishop, 2012) or patent citations (Bae and Koo, 2005), the empirical approach introduced in Colombelli (2016) and Colombelli and Quatraro (2013) has been built upon in this paper. The information contained in patent documents[5] has been used to calculate a number of variables that characterize the local knowledge base, on the basis of the complementarity, variety and similarity degree of its components. The implementation of knowledge indicators has been based on the recombinant knowledge approach.

Patents have been considered as a proxy of knowledge, and then the technological classes to which patents are assigned have been examined as the constituting elements of its structure. Each technological class *j* is linked to another class *m* when the same patent is assigned to both classes[6]. The higher the number of patents assigned to both classes *j* and *m*, the stronger the link. Since the technological classes that have been attributed to patents are reported in the patent document, we refer to the link between *j* and *m* as the co-occurrence of both classes within the same patent document[7].

On this basis, the following two key characteristics of a region's knowledge was calculated:

a) Knowledge variety (KV), which measures the degree of technological diversification of the knowledge base. It is based on the informational entropy index, and can be further decomposed into related and unrelated technological varieties (RKV and UKV, respectively).
b) Knowledge coherence (COH), which measures the average degree of complementarity among the technologies that make up the local knowledge base.

4.2.2.2 Knowledge variety

[5]The limits of patent statistics as indicators of technological activities are well known. The main drawbacks can be summarized as: their sector-specificity, the existence of non-patentable innovations and the fact that they are not the only protecting 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 feature large firms (Pavitt, 1985; Griliches, 1990). Nevertheless, previous studies highlighted the usefulness of patents as measures of production of new knowledge. Such studies show that patents represent very reliable proxies for knowledge and innovation, compared to analyses that draw upon surveys that have directly investigated 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 to the use of patents as a good proxy of technological activities (Hall et al., 1986).

[6] 4-digit technological classes have been used in the calculation.

[7]It should be stressed that in order to compensate for the intrinsic volatility of patenting behaviour, each patent application has been made to last five years in order to reduce the noise induced by changes in the technological strategy.

Previous research on the diversity of the knowledge source of EIs focused on the breadth index (Ghisetti et al., 2015), which was defined as the number of information sources that are valuable for firms going green. In this paper, we have instead focused on the breadth of the local knowledge base as a factor of influence on the grasping of unexploited technological opportunities by prospective green entrepreneurs. For this reason, a measure of technological differentiation has been considered.

The measurement of knowledge variety is based on the information entropy index. Entropy measures the degree of disorder of the system; systems characterized by high entropy are characterized by high degrees of uncertainty (Saviotti, 1988). Informational entropy is a diversity measure that shows some interesting properties (Frenken and Nuvolari, 2004), including multidimensionality. This is particularly relevant for our purposes, as it allows an entropy index to be built up on the distribution of the co-occurrences of technological classes in patents, instead of considering the distributions of the single technological classes.

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

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

Therefore, the measure of multidimensional entropy considers the variety of co-occurrences of technological classes within patent applications, and provides an index of to what extent the creation of new knowledge is focused on narrower sets 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-group entropy measures the average degree of variety within the subsets; between-group entropy focuses on the subsets, and measures the variety across them. Let the technologies *i* and *j* belong to the *g* and *z* subsets of the classification scheme, respectively. If $l \in S_g$ and $j \in S_z$ (g = 1,…,G; z = 1,…, Z), we can write:

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

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

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

Finally, the (weighted) within-group entropy can be written as follows:

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

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

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

The within-group entropy (or related variety) measures the degree of technological differentiation within the macro-field, while the between-group (or unrelated) variety measures the degree of technological differentiation across the 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.

The between- and within-entropy can be labelled as *unrelated knowledge variety* (*UKV*) and *related knowledge variety* (*RKV*), respectively, while the total information entropy is referred to as *general knowledge variety (KV)* (Frenken et al., 2007; Boschma and Iammarino, 2009). When the variety is high (low), it is possible to state that the search process has been extensive (partial).

4.2.2.3 Knowledge coherence

Coherence is defined as the average relatedness of a technology chosen randomly within a firm's patent portfolio, with respect to any other technology (Nesta and Saviotti, 2006; Nesta, 2008; Quatraro, 2010).

Obtaining the knowledge coherence index requires a number of steps. First, it is necessary 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 i and j technologies, τ_{lj} (see Quatraro, 2010).

The weighted average relatedness, WAR_l is then obtained as the degree to which technology l is related to all the other $j \in l$ technologies in the region's patent portfolio, weighted by patent count P_{jt}:

$$WAR_{lt} = \frac{\sum_{j \neq 1} \tau_{lj} P_{jt}}{\sum_{j \neq 1} P_{jt}} \tag{7}$$

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

$$COH_t = \sum_l \mathrm{WAR}_{lt} \times \frac{\mathrm{P}_{lt}}{\sum_l \mathrm{P}_{lt}} \qquad (8)$$

It should be noted that this index, which is implemented by analysing the co-occurrence of the technological classes within patent applications, 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.

4.2.3 Control variables

Apart from the effects of the knowledge indicators, (we also control for) a number of factors are controlled, which, according to the extant literature, are likely to affect the formation of a new firm.

First, the possibility of reaping the economic benefits that stem from the presence of potentially high demand levels can influence the choice of running a new firm in a specific place. For this reason, the effects of agglomeration economies (POP_DENS), proxied by the population density, have been controlled at the NUTS 3 level by dividing the total population at time t in region i by the land use area:

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

Second, agglomeration economies can also stem from the presence of other firms in the same place, and this ensures, to some extent, the availability of local markets for intermediate goods. For this reason, the firm density (FIRM_DENS), calculated as the ratio between the number of registered firms at time t in region i and the land use area, has been added as a control variable:

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

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, 2002; Bonaccorsi et al. 2013).

Third, the creation of new firms can be the outcome of an 'escape from unemployment' strategy. Consistently, the unemployment rate at the NUTS 3 level (UNEM), calculated as the ratio between the number of unemployed people and the number of individuals in the labour force at time *t* in region *has also been controlled.*

Fourth, the number of incubators (INC) in each province has been calculated. Business incubators in fact represent a key resource for the creation of new firms, as they provide the necessary conditions for successful undertakings and increase the likelihood of survival (Colombo and Delmastro, 2002; Auricchio et al., 2014).

Fifth, a large body of literature has stressed the importance of international trade, and in particular of exports, for the creation of new ventures. In reality, high degrees of internationalization may engender the dynamics of 'learning by exporting', based on knowledge on new market and technological opportunities from foreign countries (Blalock and Gertler; 2004; Branstetter 2006; Hessels and van Stel, 2011). For this reason, a variable that takes into consideration the internationalization degree of the NUTS3 region *i* at time *t* has been included in the analysis. The (EXPORT) variable is taken from the Italian Institute of Statistics (ISTAT), and is calculated as the share of the value of regional exports in 'dynamic' sectors over the total exports[8].

Sixth, 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 investment 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 who cannot rely on personal wealth (Stiglitz and Weiss, 1981; Evans and Jovanovic, 1989; Johansson, 2000). In line with this literature, a variable (FIN_SYSTEM) that takes into consideration the quality of the financial markets in the NUTS 3 regions, and which is proxied by the rate of decay of investments, has been included in the econometric model.

Seventh, the role of different kinds of university knowledge in the creation of new ventures has been documented by previous literature, such as knowledge embedded in university graduates (Harhoff 1999; Woodward et al. 2006; Kirchhoff et al. 2007; Acosta et al. 2011). Moreover, a large body of literature has investigated the phenomenon of student start-ups as a significant part of overall high-tech university based entrepreneurship (Bergmann et al., 2016). For this reason, we

[8] 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.

include the share of graduates in the labour force (GRADUATES) as a control variable in our empirical framework.

Finally, 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 the composition of the local industrial structure, and in particular on for the weight of innovative activities, a variable proxing for the presence of high tech business sectors in the local environment (HTKIS) has been included in the analysis.

4.3 Methodology

The basic hypothesis given in section 2 is that the properties of the local knowledge base can exert an influence on the creation of ERT start-ups in view of the KSTE. The test of such a hypothesis needs the dependent variable $ERT_{i,t}$ to be modelled as a function of the characteristics of the knowledge base. The discrete nature and non-negative nature of such a dependent variable suggests the adoption of estimation techniques for *count data* models. The equality between conditional variance and conditional mean in the distribution of the dependent variable was violated in these models, suggesting the need for a Negative Binomial class of models instead of a Poisson one.

In the present case, the analysis of the determinants of $ERT_{i,t}$ has posed an additional problem, due to the excess time-region combination, for which $ERT_{i,t}$=0, as discussed in Section 4.2.1. This leads to a situation in which (we observe) an "excess of zeros" can be observed in the dependent variables, and an investigation is necessary to establish whether the observed zeros are due to the overall absence of innovative start-ups or to a specific lack of green start- ups in time-regions that somehow feature a certain degree of innovative start-up dynamics. The zero-inflated negative binomial (ZINB) model is more appropriate in this case to fit the data, since it allows empirical frameworks to be modelled in which the excess of zeros in the dependent variables is generated by a different process than the count values. This model simultaneously runs two equations: a binary logistical equation to model the zeros in the dependent variables and a count data estimation (negative binomial or Poisson) to model the count data dependent variables. In our specific case, the LOGIT equation allows a discrimination to be made between the zeros due to Regions in which some start-ups are created, but where there are no green start-ups, and those due to Regions that have not created any kind of innovative start-ups, *green* or otherwise. In other words, our inflation equation (the LOGIT part of the model) has been based on a variable

(*TotStartups*) that captures the overall number of innovative start-ups (irrespective of whether these were ERT or not) in each time-region combination. The Vuong test has confirmed the appropriateness of this choice, as reported in the estimation result tables[9].

To test our hypothesis, the following basic models have been specified:

$$ERT_{i,t} = \exp(a + \beta_1 KSTOCK_{i,t-n} + \boldsymbol{Z}\gamma + \sum \rho_i + \sum \psi t + \varepsilon_{i,t}) \quad (9a)$$

$$ERT_{i,t} = \exp(a + \beta_1 GTKSTOCK_{i,t-n} + \beta_2 NOGTKSTOCK_{i,t-n} + \boldsymbol{Z}\gamma + \sum \rho_i + \sum \psi t + \varepsilon_{i,t}) \quad (9b)$$

$$ERT_{i,t} = \exp(a + \beta_1 KV_{i,t-n} + \boldsymbol{Z}\gamma + \sum \rho_i + \sum \psi t + \varepsilon_{i,t}) \quad (10a)$$

$$ERT_{i,t} = \exp(a + \beta_{1R} KV_{i,t-n} + \beta_2 UKV_{i,t-n} + \boldsymbol{Z}\gamma + \sum \rho_i + \sum \psi t + \varepsilon_{i,t}) \quad (10b)$$

$$ERT_{i,t} = \exp(a + \beta_1 COH_{i,t-n} + \boldsymbol{Z}\gamma + \sum \rho_i + \sum \psi t + \varepsilon_{i,t}) \quad (10c)$$

The error term is decomposed into ρ_i, which captures the region fixed effects, the time dummies $\sum\psi t$, and the error component ε_{it}. It should be noted that different regressions have been run using different lags for the variables that proxied for the characteristics of the local knowledge base. The results of the estimations using three-year lags are reported as they are the ones that performed the best in terms of AIC and BIC. The KSTOCK variable and the other knowledge-related variables are included separately in the empirical estimations, due to the high correlation, as can be seen in Table 3.

>>> INSERT TABLE 3 ABOUT HERE <<<

The ***Z*** vector includes the control variables discussed in Section 4.2.3. Finally, it is worth noting that all explanatory variables have been transformed using an inverse hyperbolic sine transformation. In a nutshell, this transformation can be interpreted as a logarithmic transformation, but it is more appropriate when the variables assume a zero value for some observations (Burbidge et al. 1988).

5 Econometric results

The results of the econometric estimations of equation (9a) are reported in table 4. All regressions include region and time dummies. The reported coefficients are marginal effects. It is worth stressing, in this respect, that all the regressors underwent an inverse sine transformation, as

[9] It is worth noting that we have also checked for the existence of autocorrelation in the dependent variables, by means of Wooldridge's test for autocorrelation in panel data. In all cases, (we obtained) statistics of between 1.4 and 1.5 were obtained, which do/did not allow us to reject the null hypothesis of no first-order autocorrelation.

indicated in Section 4. This transformation r is equivalent to a logarithmic transformation, and hence the obtained marginal effects can be interpreted as semi-elasticities.

The first column shows the fully specified model, while the other columns indicate the consistency of the results to the exclusion of the key control variables. It should be recalled that equation (9a) has been used to test H1, i.e. the augmented KSTE hypothesis, according to which the availability of local knowledge spillovers enhances the creation of green innovative start-ups in regional contexts. The KSTOCK coefficient is actually positive and significant, thus providing support to H1. The larger the knowledge stock available in local contexts is, the larger the number of ERT start-ups. In particular, the marginal effect suggests that doubling the amount of locally available knowledge stock would result in an increase in green start-ups of about 0.290 units. The magnitude is stable across the estimated models, with the only exception of model 2, in which the GRADUATES variable has been dropped.

INSERT TABLE 4 ABOUT HERE

This result is important in that it once more highlights the relevance of the KSTE approach for the formation of green innovative start-ups. Of all the control variables, only the local share of graduates in the workforce yields a significant (and positive) coefficient. However, the magnitude of the semi-elasticity seems to be much lower than that of KSTOCK.

This result would only provide a small contribution to the extant literature. Nonetheless, it was noticed, in Section 2, that the debate on the determinants of green technologies has emphasized the importance of distinguishing between ‘clean’ and ‘dirty’ technologies, thus suggesting that the spillovers from the former are more relevant than those from the latter (Dechezlepretre et al., 2013). Table 5 therefore provides a test for H2, according to which spillovers from clean technologies are stronger than spillovers generated by dirty technologies[10]. All the regressions included region and time dummies. The econometric results are in line with this expectation, as the GT_KSTOCK coefficient is positive and significant in all of the models reported in the table, while the NOGT_KSTOCK one is positive and significant in only one out of four models, that is, in the one in which the GRADUATES variable was dropped. As for the magnitude, the semi-elasticity appears to be lower than that observed for KSTOCK in Table 4. The doubling of GT_KSTOCK is here associated with an increase in ERT of about 0.2 units.

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[10] Additional regressions have been run separately, in which GT_STOCK and NOGT_STOCK have been included. The results confirm the patterns shown in Table 5.

As a robustness check, we further refined refined the measurement of the dependent variable by checking, where possible, the activities carried out by each ERT start-up in the official list, and then flagging them as ‘green’ accordingly. The results are reported in Annex 1. Even though this procedure is not completely reliable, due to the presence of a number of firms that do not advertise their activities on the social networks or through a website, the results are in line with the previous estimations.

INSERT TABLE 5 ABOUT HERE

So far, evidence has been provided that supports the hypotheses concerning the importance of the stock of local knowledge, and in particular of the stock of local green knowledge. The next step involves investigating H3 and H4 on whether the heterogeneous nature of local knowledge matters, and to what extent. In Section 2 we in fact stressed that an increasing body of literature has studied the effect of the breadth and scope of knowledge sources for the introduction of EIs (Horbach et al., 2013; Ghisetti et al., 2015). In this paper we instead test to what extent the technological variety of local knowledge bases that underpin the creation of ERT start-ups is dispersed across disparate areas of the technological landscape, rather than across loosely related ones.

INSERT TABLE 6 ABOUT HERE

The first column in Table 6 shows the results of the estimation of the impact of knowledge variety (KV) on the generation of ERT start-ups. Based on one hand on the previous literature about KSTE, and on the other hand on the complex and systemic nature of green knowledge, the empirical results support the hypothesis according to which technological variety positively affects the creation of ERT start-ups in local contexts. Therefore, this result is consistent with H3, according to which the formation of ERT innovative start-ups is favoured by the local availability of knowledge spanning across a variety of technological domains. The coefficient suggests that doubling the knowledge variety would result in a one unit increase of green start-ups.

However, as we wish to gain further understanding on the relationship between variety and green start-ups an investigation has been conducted to establish whether the kind of implied heterogeneity involves the local accumulation of knowledge in the related and complementary technological fields or knowledge in apparently disconnected technological fields. The second column in Table 6 shows the differential impact of the related and unrelated knowledge variety

(RKV and UKV, respectively) on ERT[11]. Other things being equal, RKV yields a positive and significant coefficient, while UKV yields a positive though insignificant one. In Column (3), we instead investigate the effect of COH, the coefficient of which is positive and significant. As far as the magnitude of the marginal effects is concerned, the present results suggest that by doubling RKV, an increase in ERT of about 0.6 units would be observed, while a doubling of the coherence would result in an increase in COH of about 0.28 units. Overall, these results would seem to provide support for H4, and suggest that the creation of green start-ups emerges from local knowledge bases that are constituted by a high degree of internal coherence, i.e. by the presence of highly related technological fields.

6 Conclusions

Innovative start-ups are considered as a powerful instrument for both stagnant economies to recover and developed ones to grow. The recent financial crisis and the resulting economic downturn have in fact generated severe resource constraints and unpredictable market conditions that have significantly challenged both developed and emerging countries. Such adverse environmental conditions have fostered a greater need for rethinking the policy agenda, in both the EU and non-community countries, to boost economic growth in the years to come. In this vein, at the end of 2012, the Italian Government approved a Law Decree in which specific measures were provided to promote the creation and development of start-ups.

Less attention has been devoted, in the empirical literature, to the specific case of green start-ups. Being centered around the development and commercialization of EIs, their beneficial impact is in fact related to the win-win framework that is typical of these technologies. EIs yield positive effects on both economic and environmental performances. The understanding of their determinants is therefore of paramount importance.

The investigation is based on a theoretical framework in which KSTE is combined with the specific literature on the determinants of EIs. The appreciation of the stylized fact about the complex and systemic nature (Rennings and Rammer, 2009; Horbach et al., 2013; Ghisetti et al., 2015) of green technologies has allowed the traditional arguments included in the KSTE to be

[11] It is worth recalling that related and unrelated knowledge variety/ are not opposites, but orthogonal in their meaning (Frenken et al., 2007; Castaldi et al., 2014). In principle, a NUTS 3 region can be characterized by both high RKV and UKV. These would be regions that are diversified into unrelated technological categories, while also being diversified into many specific classes in each of these categories. . It is also worth stressing that empirically related and unrelated variety tend to correlate positively (see Table 3; see also Frenken et al., 2007; Quatraro, 2010; Quatraro, 2011; Boschma et al., 2012; Hartog et al., 2012).

refined in order to derive expectations about the relationship between local knowledge spillovers and the formation of green innovative start-ups.

In particular, we have found support for our four hypotheses. The first one states that the KSTE argument on the technological opportunities engendered by untapped locally available knowledge is somewhat important for the generation of green start-ups. This is because incumbent firms may not have the necessary technological capabilities to master such complex technologies, if they appear to be far from their core competences (De Marchi, 2012). Prospective green entrepreneurs might therefore grasp these opportunities and commercialize their green technology through the formation of innovative start-ups.

Our results also suggest that spillovers from ‘clean’ technologies matter more than spillovers from ‘dirty’ ones in shaping the generation of green start-ups. On the one hand, this could be due to the cognitive proximity of prospective green entrepreneurs to the knowledge base of green technologies, and on the other hand to another important stylized fact on these technologies, i.e. their wider scope of application (Dechezlepretre et al., 2013).

Moreover, we have found evidence of the positive association between technological variety yields and the generation of green innovative start-ups. This finding is consistent with the previous literature in which the importance of the breadth of knowledge sources for EI was emphasized (Horbach et al., 2013; Ghisetti et al., 2015). However, it should be stressed that the extant literature has focused on diversity, in terms of typologies of actors with whom firms interact for EIs, while here we have focused on the degree of related and unrelated technological diversification in local innovation dynamics.

Finally, our results show that the kind of technological variety that leads to the creation of green start-ups involves a historical process of knowledge accumulation in which the combination of related and highly complementary technological fields is privileged, and the relevance of cognitive proximity for the effective exploitation of technological opportunities in the green domain is stressed.

This paper provides the first systematic evidence on the relationship between knowledge spillovers and the creation of green innovative start-ups. Further research avenues could focus, at a micro-level, on the investigation of the individual traits of green entrepreneurs, as well as on the survival patterns of these start-ups. Further efforts should be devoted, at a meso-level, to mapping the network effects behind the formation of green startups, in order to understand the differential impact of tacit and codified knowledge, as well as the relationship with the evolution of local technological specialization patterns.

Some important limits of this study should be acknowledged. We have investigated empirical associations, but causal effects cannot be ascertained in this framework. Moreover, the considered definition of green start-ups is based on the criteria established by a law decree. In other words, this is a sort of top-down approach that risks including some startups that can only marginally be defined as innovative or green in the sample. Although we have tried to address this problem, by means of the estimations reported in Annex 1, more efforts are needed to clarify this information.

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Figure 1 – Geographical distribution of the overall and ERT innovative start-ups

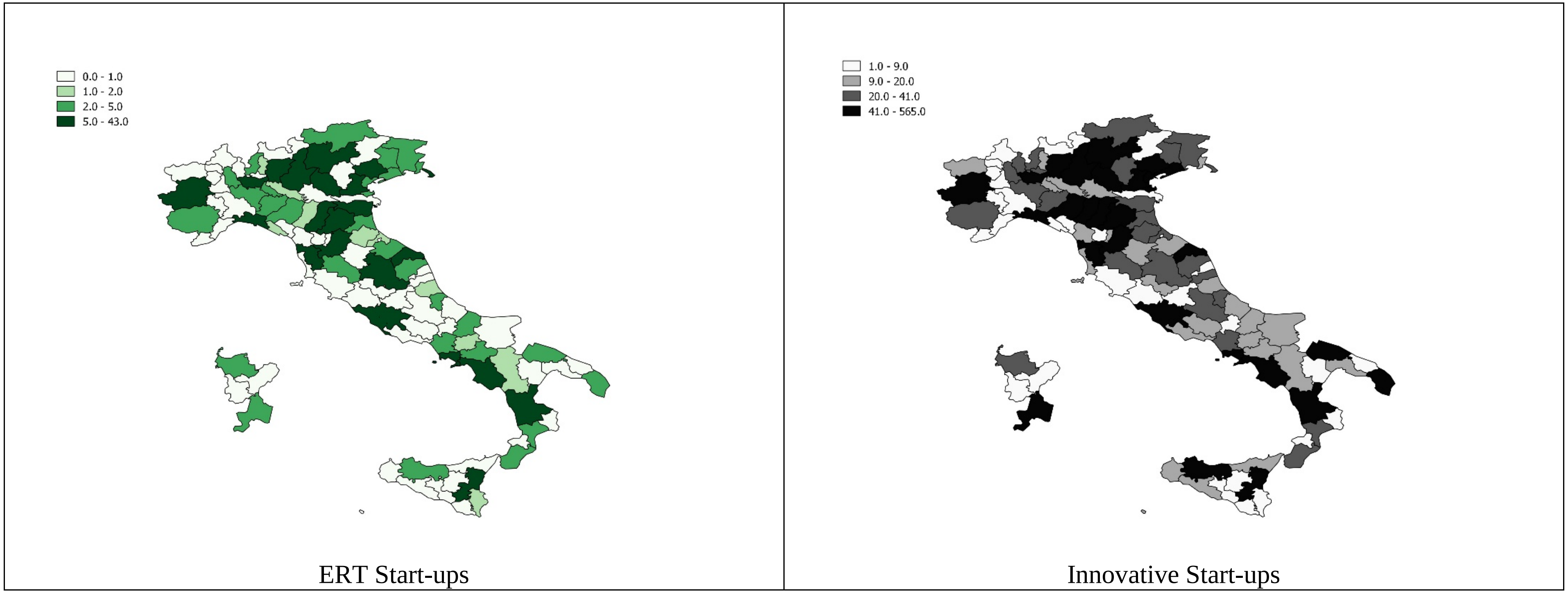


Figure 2 - Dynamics of KSTOCK, GT_STOCK, NO_GTSTOCK

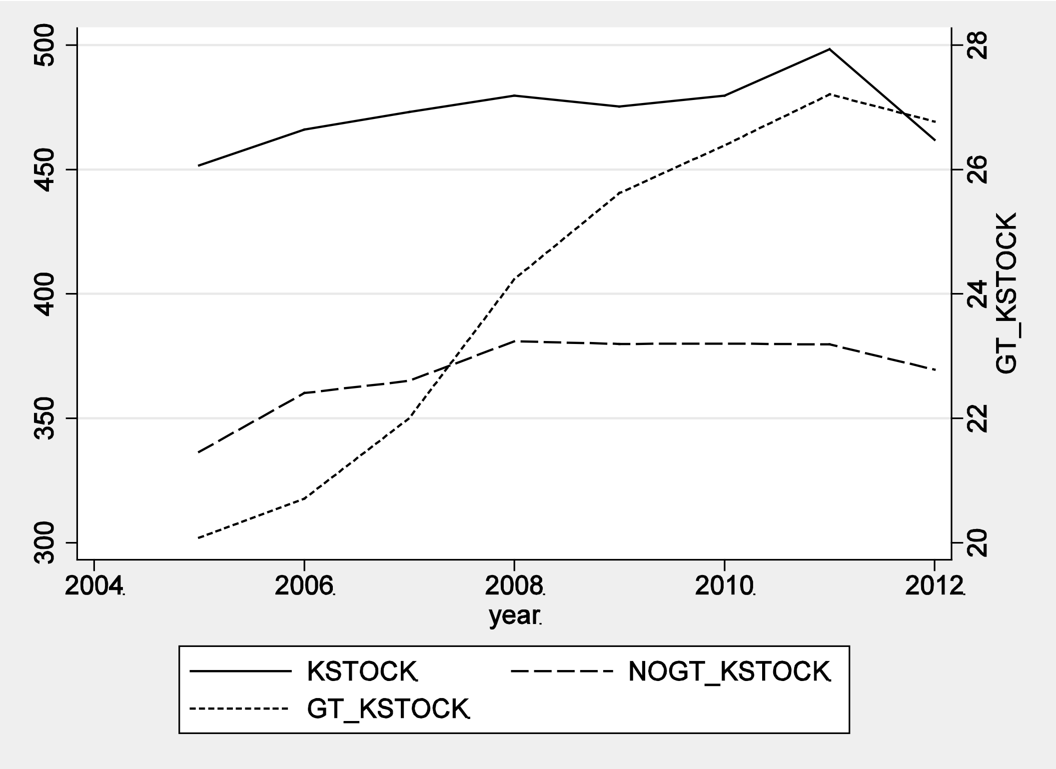


Table 1 – Time Distribution of the innovative start-ups

Year	No-ERT	ERT	Total
2009	25	4	29
2010	152	23	175
2011	271	37	308
2012	445	61	506
2013	842	101	943
2014	1,268	165	1,433
2015	473	58	531
Total	**3,476**	**449**	**3,925**

Table 2 - Descriptive statistics

Variable	N	Min	Max	Mean	Sd	Skewness	Kurtosis	Median
ERT	707	0.000	16.000	0.622	1.559	5.273	41.920	0.000
GREEN	707	0.000	10.000	0.236	0.706	5.803	60.294	0.000
KSTOCK	696	0.000	9.138	5.294	1.580	-0.349	3.241	5.326
GT_KSTOCK	676	0.000	4.248	1.089	1.026	0.530	2.380	2.936
NOGT_KSTOCK	676	0.000	6.890	3.224	1.336	-0.005	2.480	5.724
KV	684	0.000	3.114	2.421	0.503	-2.229	10.047	2.554
RKV	684	0.000	2.854	2.029	0.547	-1.626	6.311	2.167
UKV	684	0.000	1.778	1.372	0.353	-2.061	7.811	1.481
COH	693	-2.229	1.755	-0.701	0.524	1.492	6.806	-0.743
UNEMP	697	0.019	0.258	0.078	0.042	1.032	3.639	0.064
POP_DENS	699	4.338	8.562	5.922	0.765	0.788	4.566	5.898
INCUB	701	0.000	2.492	0.376	0.623	1.402	3.792	0.000
EXPORT	592	0.652	4.501	3.189	0.709	-0.557	3.329	3.192
FINANCE	600	0.241	3.053	1.072	0.396	0.552	4.164	1.031
FIRM_DENS	697	0.156	0.419	0.269	0.050	0.421	2.860	0.265
GRADUATES	701	0.000	11.273	4.278	4.457	0.143	1.133	0.000
HTKIS	504	0.002	0.010	0.005	0.001	0.492	2.999	0.005

Table 3 – Correlation matrix

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	**ERT**	1.000																
2	**GREEN**	0.737	1.000															
3	**KSTOCK**	0.352	0.284	1.000														
4	**GT_KSTOCK**	0.357	0.263	0.706	1.000													
5	**NOGT_KSTOCK**	0.302	0.213	0.931	0.696	1.000												
6	**COH**	-0.129	-0.137	-0.067	-0.101	-0.029	1.000											
7	**KV**	0.228	0.183	0.831	0.554	0.781	-0.002	1.000										
8	**RKV**	0.246	0.187	0.831	0.548	0.780	-0.013	0.961	1.000									
9	**UKV**	0.154	0.139	0.678	0.471	0.641	0.005	0.807	0.642	1.000								
10	**UNEMP**	-0.028	0.005	-0.549	-0.342	-0.573	-0.077	-0.470	-0.472	-0.425	1.000							
11	**POP_DENS**	0.284	0.213	0.489	0.403	0.475	-0.111	0.410	0.409	0.356	-0.012	1.000						
12	**FIRM_DENS**	-0.121	-0.105	-0.575	-0.388	-0.569	0.059	-0.480	-0.468	-0.477	0.676	-0.231	1.000					
13	**INCUB**	0.376	0.255	0.461	0.389	0.445	-0.075	0.331	0.362	0.204	-0.141	0.296	-0.187	1.000				
14	**GRADUATES**	0.354	0.283	0.332	0.323	0.259	-0.139	0.213	0.235	0.120	0.051	0.149	-0.021	0.419	1.000			
15	**HTKIS**	0.369	0.262	0.581	0.408	0.599	-0.041	0.453	0.470	0.414	-0.492	0.548	-0.619	0.301	0.088	1.000		
16	**EXPORT**	0.104	0.089	0.258	0.106	0.218	-0.139	0.175	0.184	0.145	-0.096	0.070	-0.127	0.287	0.199	0.108	1.000	
17	**FINANCE**	0.014	0.021	-0.336	-0.274	-0.380	-0.115	-0.337	-0.331	-0.286	0.488	-0.158	0.402	-0.161	-0.038	-0.224	-0.050	1.000

Table 4 - Zero-inflated Negative Binomial Estimation, total Knowledge Stock

	(1)	(2)	(3)	(4)
KSTOCK	0.2819***	0.4207***	0.2753***	0.2812***
	(0.0994)	(0.1173)	(0.0983)	(0.0962)
UNEMP	-4.2790	-4.7412	-4.3412	-4.2945
	(3.0975)	(3.7889)	(3.1867)	(3.0293)
POP_DENS	-0.0029	-0.0634	0.0048	
	(0.0910)	(0.1037)	(0.0937)	
INCUB	0.0523	0.1312	0.0449	0.0511
	(0.1158)	(0.1461)	(0.1237)	(0.1080)
EXPORT	0.1065	0.1392	0.1124	0.1060
	(0.0934)	(0.0999)	(0.0978)	(0.0947)
FINANCE	-0.2065	-0.1716	-0.2130	-0.2060
	(0.2200)	(0.2444)	(0.2217)	(0.2183)
FIRM_DENS	-1.4762	-1.9309		-1.4692
	(2.6020)	(2.7458)		(2.6433)
GRADUATES	0.0630**		0.0634**	0.0630**
	(0.0204)		(0.0209)	(0.0200)
HTKIS	0.079	0.078	0.083*	0.079*
	(0.052)	(0.052)	(0.050)	(0.050)
inflate				
TotStartups	0.0397***	0.0433***	0.0400***	0.0397***
	(0.0072)	(0.0073)	(0.0072)	(0.0072)
lnalpha	-3.6078**	-3.1764**	-3.6533*	-3.6127**
	(1.478)	(1.3039)	(1.9296)	(1.8398)
Regional dummies	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes
N	494	494	494	494
AIC	864.1022	874.0574	862.5443	862.1078
BIC	1011.1909	1016.9436	1005.4305	1004.9940
Log Lik	-397.0511	-403.0287	-397.2722	-397.0539
Mean VIF	2.01	1.98	1.82	1.87
McFadden's R2	0.2969	0.2863	0.2965	0.2969
Vuong test	2.8941	3.2385	2.8829	2.8938

Dependent Variable: ERT
Marginal effects
NUTS3 clustered standard errors are reported in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5- Zero-inflated Negative Binomial Estimation, clean vs. 'dirty' knowledge stock

	(1)	(2)	(3)	(4)
GT_KSTOCK	0.2391**	0.3168**	0.2420**	0.2285**
	(0.1061)	(0.1153)	(0.1062)	(0.1028)
NOGT_KSTOCK	0.1749	0.2462	0.1672	0.1740
	(0.1414)	(0.1861)	(0.1361)	(0.1388)
UNEMP	-4.6134	-5.1149	-4.6431	-4.8341
	(3.0974)	(3.8300)	(3.1682)	(2.9425)
POP_DENS	-0.0428	-0.1061	-0.0377	
	(0.0930)	(0.1023)	(0.0952)	
INCUB	-0.0279	0.0220	-0.0325	-0.0434
	(0.1307)	(0.1626)	(0.1383)	(0.1242)
EXPORT	0.1513	0.1941*	0.1547	0.1409
	(0.0896)	(0.0920)	(0.0931)	(0.0894)
FINANCE	-0.2546	-0.2249	-0.2559	-0.2453
	(0.2467)	(0.2721)	(0.2476)	(0.2459)
FIRM_DENS	-0.9612	-1.3009		-0.8635
	(2.6687)	(2.8202)		(2.6762)
GRADUATES	0.0557**		0.0559**	0.0571**
	(0.0201)		(0.0204)	(0.0198)
HTKIS	0.095**	0.102**	0.098**	0.089**
	(0.052)	(0.052)	(0.050)	(0.050)
inflate				
TotStartups	0.0456***	0.0530***	0.0456***	0.0456***
	(0.0084)	(0.0101)	(0.0083)	(0.0084)
lnalpha	-4.5842	-3.3648**	-4.6541	-4.5945
	(4.2889)	(1.5175)	(4.5948)	(4.3478)
Regional dummies	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes
N	494	494	494	494
AIC	854.5281	865.7405	852.5988	852.5818
BIC	1005.1574	1012.1857	999.0440	999.0270
Mean VIF	2.19	2.19	2.05	2.06
Log Lik	-391.2640	-397.8703	-391.2994	-391.2909
McFadden's R2	0.2991	0.2872	0.2990	0.2990
Vuong test	2.8966	3.2311	2.8990	2.8926

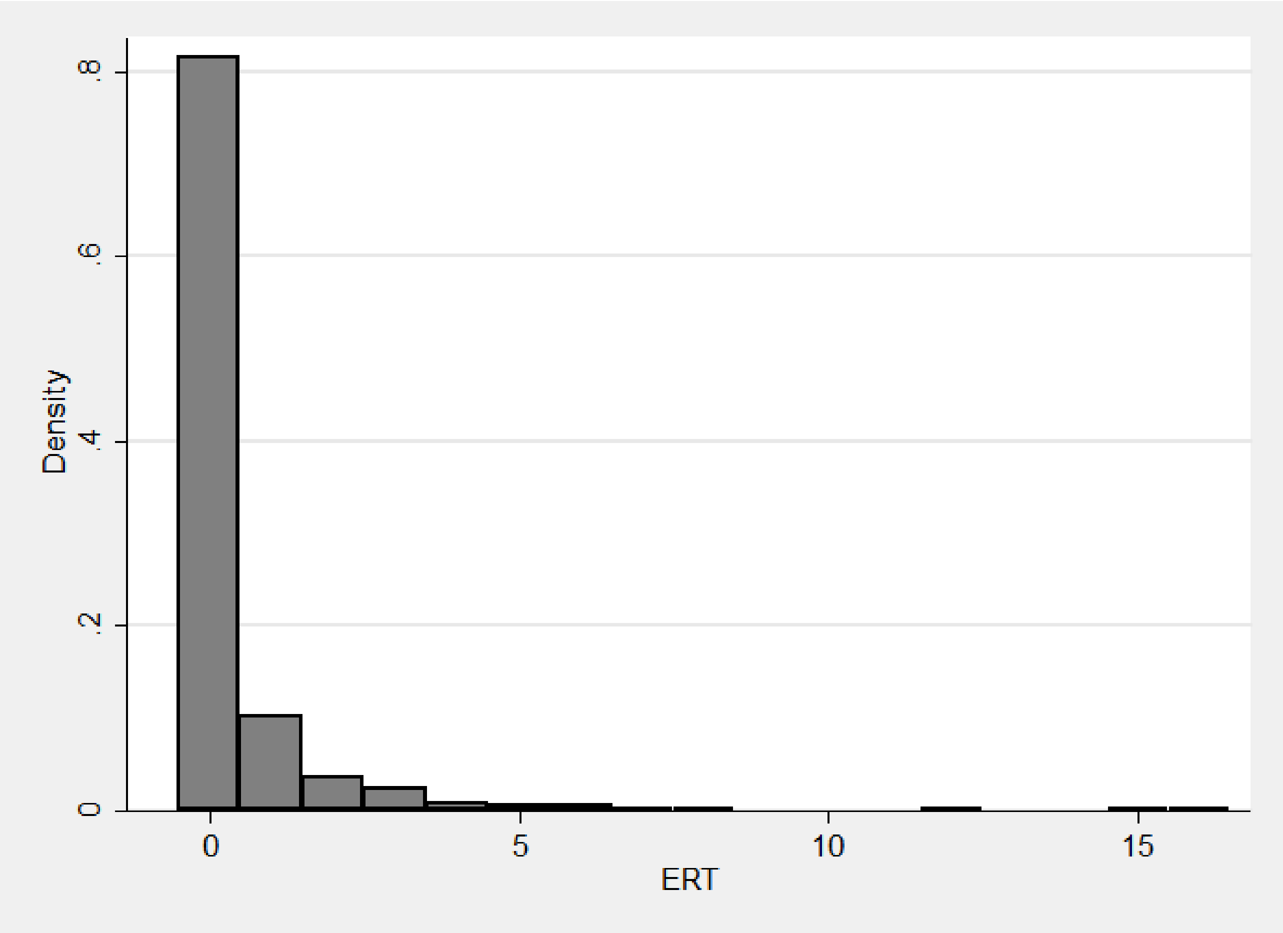
Dependent variable: ERT
Marginal effects
NUTS3 clustered standard errors are reported in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6 - Zero-inflated Negative Binomial Estimation, Knowledge variety and coherence

	(1)	(2)	(3)
KV	0.9644***		
	(0.2996)		
RKV		0.6028**	
		(0.2716)	
UKV		0.4724	
		(0.4126)	
COH			0.2770**
			(0.1290)
UNEMP	-4.9456	-4.9525	-6.5725
	(3.2744)	(3.2565)	(3.5351)
POP_DENS	0.0032	0.0074	0.1692
	(0.0979)	(0.0996)	(0.1047)
INCUB	0.1503	0.1459	0.1628
	(0.1185)	(0.1219)	(0.1230)
EXPORT	0.1001	0.0976	0.0977
	(0.0953)	(0.0952)	(0.0951)
FINANCE	-0.1351	-0.1712	-0.1671
	(0.2130)	(0.2508)	(0.1894)
FIRM_DENS	-0.7929	-0.6131	-1.2969
	(2.6449)	(2.6168)	(2.7930)
GRADUATES	0.0724***	0.0732***	0.0858***
	(0.0209)	(0.0209)	(0.0201)
HTKIS	0.098	0.099	0.077
	(0.056)	(0.055)	(0.056)
inflate			
TotStartups	0.0421***	0.0418***	0.0474***
	(0.0074)	(0.0073)	(0.0073)
lnalpha	-3.3639**	-3.5650**	-3.3787**
	(1.4641)	(1.7974)	(1.4939)
Regional dummies	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes
N	494	494	494
AIC	866.3730	868.2591	871.5852
BIC	1012.8903	1018.9626	1018.6030
Mean VIF	1.67	1.81	1.88
Log Lik	-398.1865	-398.1295	-400.7926
McFadden's R2	0.2909	0.2910	0.2898
Vuong test	3.2365	3.1895	3.6063

Dependent variable: ERT
Marginal effects
NUTS3 clustered standard errors are reported in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Annex 1 - Density Estimation of ERT



Annex 2 - Zero-inflated Negative Binomial Estimation, subsample of 'green' ERT

	(1)	(2)	(3)	(4)
GT_KSTOCK	0.0908*	0.0904*	0.0870*	0.0927*
	(0.0539)	(0.0539)	(0.0529)	(0.0535)
NOGT_KSTOCK	0.0065	0.0621	0.0097	0.0107
	(0.0672)	(0.0603)	(0.0662)	(0.0658)
UNEMP	-2.5099	-3.3137	-2.5960	-2.4809
	(2.4401)	(2.4157)	(2.4137)	(2.4352)
POP_DENS	0.0234	0.0017	0.0240	
	(0.0671)	(0.0660)	(0.0662)	
INCUB	-0.0597	-0.0272	-0.0564	-0.0498
	(0.0717)	(0.0614)	(0.0718)	(0.0653)
EXPORT	0.0916	0.1174	0.0949	0.0972
	(0.0728)	(0.0710)	(0.0721)	(0.0709)
FINANCE	-0.1675	-0.1320	-0.1644	-0.1721
	(0.1347)	(0.1306)	(0.1341)	(0.1338)
FIRM_DENS	-0.9392	-0.8999		-0.9460
	(1.4894)	(1.4831)		(1.4826)
GRADUATES	0.0254**		0.0248**	0.0247**
	(0.0108)		(0.0107)	(0.0105)
HTKIS	-0.0004	0.0055	0.0012	0.0025
	(0.0372)	(0.0361)	(0.0368)	(0.0362)
Inflate				
TotStartups	0.0189*	0.0209**	0.0190*	0.0190*
	(0.0038)	(0.0039)	(0.0038)	(0.0038)
Regional dummies	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes
lnalpha	-4.1805	-3.1438	-3.5959	-4.0871
	(6.1691)	(2.4137)	(3.5665)	(5.6511)
N	485	485	485	485
AIC	475.0765	479.8711	473.4829	473.1985
BIC	625.7059	626.3163	619.9281	619.6437
Mean VIF	2.19	2.19	2.05	2.06
Log Lik	-201.5383	-204.9356	-201.7414	-201.5992
McFadden's R2	0.3308	0.3195	0.3301	0.3306
Vuong test	2.6040	2.2419	2.6243	2.6152

Dependent variable: GREEN
Marginal effects
NUTS3 clustered standard errors are reported in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Annex 3 - WIPO Green Inventory, List of Technological Classes

TOPIC	IPC
ALTERNATIVE ENERGY PRODUCTION	
Bio-fuels	
Solid fuels	C10L 5/00, 5/40-5/48
Torrefaction of biomass	C10B 53/02
	C10L 5/40, 9/00
Liquid fuels	C10L 1/00, 1/02, 1/14
Vegetable oils	C10L 1/02, 1/19
Biodiesel	C07C 67/00, 69/00
	C10G
	C10L 1/02, 1/19
	C11C 3/10
	C12P 7/64
Bioethanol	C10L 1/02, 1/182
	C12N 9/24
	C12P 7/06-7/14
Biogas	C02F 3/28, 11/04
	C10L 3/00
	C12M 1/107
	C12P 5/02
From genetically engineered organisms	C12N 1/13, 1/15, 1/21, 5/10, 15/00 A01H
Integrated gasification combined cycle (IGCC)	C10L 3/00
	F02C 3/28
Fuel cells	H01M 4/86-4/98, 8/00-8/24, 12/00-12/08
Electrodes	H01M 4/86-4/98
Inert electrodes with catalytic activity	H01M 4/86-4/98
Non-active parts	H01M 2/00-2/04 , 8/00-8/24
Within hybrid cells	H01M 12/00-12/08
Pyrolysis or gasification of biomass	
	C10B 53/00
	C10J
Harnessing energy from manmade waste	
Agricultural waste	C10L 5/00
Fuel from animal waste and crop residues	C10L 5/42, 5/44
Incinerators for field, garden or wood waste	F23G 7/00, 7/10
Gasification	C10J 3/02, 3/46
	F23B 90/00
	F23G 5/027
Chemical waste	B09B 3/00
	F23G 7/00
Industrial waste	C10L 5/48
	F23G 5/00, 7/00

TOPIC	IPC
Using top gas in blast furnaces to power pig-iron production	C21B 5/06
Pulp liquors	D21C 11/00
Anaerobic digestion of industrial waste	A62D 3/02
	C02F 11/04, 11/14
Industrial wood waste	F23G 7/00, 7/10
Hospital waste	B09B 3/00
	F23G 5/00
Landfill gas	B09B
Separation of components	B01D 53/02, 53/04, 53/047, 53/14, 53/22, 53/24
Municipal waste	C10L 5/46
	F23G 5/00
Hydroenergy	
Water-power plants	E02B 9/00-9/06
Tide/Tidal or wave power plants	E02B 9/08
Machines or engines for liquids	F03B
	F03C
Using wave or tide/tidal energy	F03B 13/12-13/26
Regulating, controlling or safety means of machines or engines	F03B 15/00-15/22
Propulsion of marine vessels using energy derived from water movement	B63H 19/02, 19/04
Ocean thermal energy conversion (OTEC)	F03G 7/05
Wind energy	F03D
Structural association of electric generator with mechanical driving motor	H02K 7/18
Structural aspects of wind turbines	B63B 35/00
	E04H 12/00
	F03D 11/04
Propulsion of vehicles using wind power	B60K 16/00
Electric propulsion of vehicles using wind power	B60L 8/00
Propulsion of marine vessels by wind-powered motors	B63H 13/00
Solar energy	
Photovoltaics (PV)	
Devices adapted for the conversion of radiation energy into electrical energy	H01L 27/142, 31/00-31/078 H01G 9/20
	H02N 6/00
Using organic materials as the active part	H01L 27/30, 51/42-51/48
Assemblies of a plurality of solar cells	H01L 25/00, 25/03, 25/16, 25/18, 31/042
Silicon; single-crystal growth	C01B 33/02 C23C 14/14, 16/24 C30B 29/06
Regulating to the maximum power available from solar cells	G05F 1/67
Electric lighting devices with, or rechargeable with, solar cells	F21L 4/00
	F21S 9/03
Charging batteries	H02J 7/35

Dye-sensitised solar cells (DSSC)	H01G 9/20
	H01M 14/00
Use of solar heat	F24J 2/00-2/54
For domestic hot water systems	F24D 17/00
For space heating	F24D 3/00, 5/00, 11/00, 19/00
For swimming pools	F24J 2/42
Solar updraft towers	F03D 1/04, 9/00, 11/04 F03G 6/00
For the treatment of water, waste water or sludge	C02F 1/14
Gas turbine power plants using a solar heat source	F02C 1/05
Hybrid solar thermal-PV systems	H01L 31/058
Propulsion of vehicles using solar power	B60K 16/00
Electric propulsion of vehicles using solar power	B60L 8/00
Producing mechanical power from solar energy	F03G 6/00-6/06
Roof covering aspects of energy collecting devices	E04D 13/00, 13/18
Steam generation using solar heat	F22B 1/00
	F24J 1/00
Refrigeration or heat pump systems using solar energy	F25B 27/00
Use of solar energy for drying/to dry materials or objects	F26B 3/00, 3/28
Solar concentrators	F24J 2/06
	G02B 7/183
Solar ponds	F24J 2/04
Geothermal energy	
Use of geothermal heat	F01K
	F24F 5/00
	F24J 3/08
	H02N 10/00
	F25B 30/06
Production of mechanical power from geothermal energy	F03G 4/00-4/06, 7/04
Other production or use of heat, not derived from combustion, e.g. natural heat	F24J 1/00, 3/00, 3/06
Heat pumps in central heating systems using heat accumulated in storage masses	F24D 11/02
Heat pumps in other domestic- or space-heating systems	F24D 15/04
Heat pumps in domestic hot-water supply systems	F24D 17/02
Air or water heaters using heat pumps	F24H 4/00
Heat pumps	F25B 30/00
Using waste heat	
To produce mechanical energy	F01K 27/00
Of combustion engines	F01K 23/06-23/10
	F01N 5/00
	F02G 5/00-5/04
	F25B 27/02
Of steam engine plants	F01K 17/00, 23/04
Of gas-turbine plants	F02C 6/18
As a source of energy for refrigeration plants	F25B 27/02
For the treatment of water, waste water or sewage	C02F 1/16
Recovery of waste heat in paper production	D21F 5/20
For steam generation by exploitation of the heat content of hot heat carriers	F22B 1/02
Recuperation of heat energy from waste incineration	F23G 5/46
Energy recovery in air conditioning	F24F 12/00
Arrangements for using waste heat from furnaces, kilns, ovens or retorts	F27D 17/00
Regenerative heat-exchange apparatus	F28D 17/00-20/00
Of gasification plants	C10J 3/86
Devices for producing mechanical power from muscle energy	F03G 5/00-5/08

ENERGY CONSERVATION	
Storage of electrical energy	B60K 6/28
	B60W 10/26
	H01M 10/44-10/46
	H01G 9/155
	H02J 3/28, 7/00, 15/00
Power supply circuitry	H02J
With power saving modes	H02J 9/00
Measurement of electricity consumption	B60L 3/00
	G01R
Storage of thermal energy	C09K 5/00
	F24H 7/00
	F28D 20/00, 20/02
Low energy lighting	
Electroluminescent light sources (e.g. LEDs, OLEDs, PLEDs)	F21K 99/00
	F21L 4/02
	H01L 33/00-33/64, 51/50 H05B 33/00
Thermal building insulation, in general	E04B 1/62, 1/74-1/80, 1/88, 1/90
Insulating building elements	E04C 1/40, 1/41, 2/284-2/296
For door or window openings	E06B 3/263
For walls	E04B 2/00
	E04F 13/08
For floors	E04B 5/00
	E04F 15/18
For roofs	E04B 7/00
	E04D 1/28, 3/35, 13/16
For ceilings	E04B 9/00
	E04F 13/08
Recovering mechanical energy	F03G 7/08
Chargeable mechanical accumulators in vehicles	B60K 6/10, 6/30
	B60L 11/16