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Innovation, appropriation and new firm formation in European regions

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Abstract
The paper examines to what extent innovation activities foster new firm formation across regions and industries in Europe. Combining data on firm formation, patenting and trademarks, it analyses new firm entries (2001-2009) in over 290 NACE industries in more than 1000 regions (NUTS 3 level). We construct a technology similarity index between industries to examine the different role of knowledge spillovers from the own industry versus technologically related industries and analyse the moderating role played by appropriation strategies through trademark registrations. We find a positive effect of incumbents' patent stocks on new firm formation in related industries, whereas the impact of incumbent patenting in the same industry of the entrant is less obvious. More intensive trademark policies by incumbents negatively moderate the effects of local knowledge stocks.

Keywords: Agglomeration externalities, Entrepreneurship, Innovation, Intellectual Property Rights, New Firm formation, Entry.

Introduction

Entrepreneurship and the creation of new firms are increasingly linked with economic growth. New firms have been recognized as important contributors to the evolution of the regional economic structures (Geroski 1991). High levels of entry are seen as a sign of economic vitality of regions (Lee et al. 2004). Support for new firm formation is put high in the priorities lists of national and regional governments. Therefore, it is important to understand factors that drive regional differences between the rates of new firm formation. Increasing attention is given to the impact of knowledge and innovation intensity of incumbents on new firm formation in close vicinity. Although regional innovation by incumbents is seen as an important source of entrepreneurial opportunities, to date empirical results to corroborate this view have been mixed (Knoben et al. 2011) (Tsvetkova 2015) (Jofre-Monseny et al. 2011).

On the one hand, uncertainty, information asymmetries, and high transaction costs inherent to knowledge induce divergent views as regards its value, which may create new business opportunities for third parties (Malerba 2007; Christensen 2012; Acs et al. 2009; Acs et al. 2009). On the other hand, incumbent firms will aim to shield knowledge from direct rivals and potential entrants in order to increase appropriation (Belderbos & Somers 2015) and to improve their competitive position towards existing or potential competitors (Bloom et al. 2013). Due to tacitness of knowledge (Polanyi 1966a) *spatial* proximity determines to a large extent the direction of entrepreneurial search and selection (Kogut & Zander 1992), while *cognitive* proximity is important for the discovery and exploitation of new entrepreneurial opportunities (Van Oort & others 2013; Boschma 2005). Knowledge externalities may occur in the *same* or closely *related* industries (Glaeser et al. (1991) - following the notion of agglomeration due to Marshall (1920), Arrow (1971) and Romer (1986)- or they may occur due to knowledge diversity across industries (Jacobs (1970), with so far little conclusive evidence on the most salient spillover mechanism (Beaudry & Schiffauerova 2009).

The current paper contributes an analysis of new firm formation across regions and industries in Europe to shed new light on these issues. We examine the differential impact of knowledge produced locally on new firms' formation depending on technological relatedness between industries and the appropriation strategies and market rivalry between incumbents and new firms. Our research builds upon a unique and detailed dataset combining information on firm formation (ORBIS), patenting (PATSTAT) and trademarks (national trademark registries of 12 EU member states) and we analyse new firm entries (2001-2009) in over 290 NACE (4 digits) manufacturing industries in more than 1000 European regions (NUTS 3 level). We distinguish local knowledge stocks (measured by patenting activity) in the industry of the entrant from local knowledge stocks in *technologically related* industries, using a technology similarity index, based on patterns of patenting in the same IPC subclasses by firms active in different industries (Jaffe 1986)). Appropriation strategies are captured by interaction variable between patent and trademark holdings of incumbent firms.

Results confirm a positive effect of incumbents' patent stocks on new firm formation in related industries, whereas the impact of incumbent patenting in the same industry of the entrant is less obvious. More intensive trademark policies by incumbents negatively moderate the effects of local knowledge stocks. These findings are consistent with the notion of new firms avoiding head-on competition with incumbents but also benefiting from their innovation activities in exploiting new market niches.

Background and related literature

Innovation and start-ups

Understanding the determinants of new firm startups has been at the core of the industrial organisation literature. In a traditional view entry is the result of a level of profitability in excess of the long-run equilibrium (Geroski 1991). Startups enter the market to produce more of already existing homogenous goods, thereby restoring price and profit equilibria (Marshall 1920). While empirical studies found that entry rates are indeed relatively high in fast-growing and profitable industries and relatively low in industries where incumbents have absolute cost advantages or with high capital requirements (Lipczynski et al. 2005), entry is associated with much larger variation than profits, and entry rates are hard to explain by usual measures of profitability and entry barriers (Geroski (1995).

Based on a more evolutionary perspective, the focus of attention is increasingly on innovation activities of incumbent firms and knowledge spillovers in explaining entry rates. Business opportunities may arise from the incumbents' innovation processes. The knowledge they create is often underutilized by the incumbent organization, due to the uncertainty related to their economic exploitation. Uncertainty, information asymmetries, and high transaction costs inherent to knowledge induce divergent views with respect to the value of the created knowledge (Hayek 1945)(Alchian 1950) (Arrow 1962). Therefore, given uncertain prospects of novel technologies and limited resources, even large incumbents will leave open some business opportunities related to knowledge for exploration and exploitation by other economic agents (Christensen 2012), thereby fostering entry of new firms (Malerba 2007; Christensen 2012; Acs et al. 2009; Acs et al. 2009). Spillover of knowledge resulting in new entrepreneurial opportunities inducing entrepreneurs to start a new firm is a crucial point of knowledge spillover theory of entrepreneurship (KSTE) (Acs et al. 2009) and related knowledge spillover-based strategic entrepreneurship (KSSE) (Agarwal et al. 2007). KSTE posits that *"entrepreneurial opportunities do not appear to be exogenous but rather systematically created by a high presence of knowledge spillovers"* (Acs et al. 2009).

Innovation activities of incumbent organizations in this way generate knowledge spillovers - external benefits from knowledge that are enjoyed by parties other than the entity investing in the knowledge creation (Griliches 1992; Agarwal et al. 2010). The non-rival and non-excludable character of knowledge, linked to its intangible nature, make it more likely to be subject to spillovers than other investments (Arrow 1962; Romer 1990).

Knowledge spillovers and geographical proximity

In spite of rapid growth of new technologies of communication, knowledge spillovers appear to remain to a large extent a local phenomenon. Therefore, *local* knowledge pools and innovation activities of incumbent organisations are important to consider.

Geographical stickiness of knowledge is due to the crucial importance of *know-how* for manufacturing. Know-how has been defined by von Hippel (1988) as *"accumulated practical skill or expertise that allows one to do something smoothly and efficiently"*. Know-how, in contrast to *information*, is to a large extent tacit, difficult to codify and interpret (Polanyi 1966b) (Hidalgo 2015). While the marginal cost of transmitting information across space is virtually zero, the marginal cost of transmitting know-how rises with distance (Audretsch 2007).

Thanks to increased interactions between employees, ideas are disseminated among neighboring firms (Glaeser et al. 1991). Transmission and accumulation of tacit knowledge, requires direct and regular interpersonal contacts (Maskell & Malmberg 1999) because, individuals know more than they are able to explain (Polanyi (1966b). The amount of know-how that can be absorbed by individual or even an individual firm is limited. Therefore complex technical knowledge is embodied in large regional networks, rather than individual firms or persons (Hidalgo 2015). The experiential and social nature of know-how transmission and learning drive knowledge accumulation towards domains related to those already present in the vicinity. Spatial proximity is therefore also an important factor conditioning the direction of the entrepreneurial search and selection (Kogut & Zander 1992).

According to Malmberg & Maskell (2002) clusters indeed exist because co-location of firms reduces costs related to the identification, access and transfer of knowledge. But in addition to knowledge spillovers, advantages of labor market pooling and input sharing were also identified as important factors contributing to geographical agglomeration (Marshall 1920), leading to agglomeration economies.

Knowledge spillovers and cognitive proximity

Besides geographical proximity, other dimensions of proximity, including institutional, cultural, social and cognitive are at least as important for knowledge spillovers to occur and foster entry (Van Oort & others 2013; Boschma 2005). Regarding the latter, there are competing theories which formulate different predictions as to whether *homogeneity* of the clustering industries or rather *diversity* promotes economic growth (Beaudry & Schiffauerova 2009).

On the one hand, Marshall (1920), Arrow (1971) and Romer (1986) hypothesize that the concentration of an industry enhances knowledge spillovers and promotes innovation in a region. In accordance with Marshall-Arrow-Romer model formalized by Glaeser et al.

(1991), knowledge externalities and spillovers occur mainly between the firms active in the same or very similar industries. The arguments regarding the intra-industry strength of knowledge spillovers are shared by Porter (1990). This hypothesis is known as urbanization economies (Beaudry & Schiffauerova 2009).

On the other hand, Jacobs (1970) claims that knowledge spillovers often occur between distinct industries and that they are more important to the economic growth than intra-industry knowledge externalities. She argues that economic expansion occurs when novel features are added to the particular chunks of work within old technology. A diverse economic structure on a given territory fosters exchange of knowledge between seemingly different industries, which share and recombine each other's ideas. This hypothesis is known as urbanization economies (Beaudry & Schiffauerova 2009).

Building on Jacobs' theory, Frenken et al. (2005) argue that it is not mere presence of different industrial sectors that is beneficial for economic growth, but for different industries to be able to benefit from their collocation there should be some shared sphere of competences. Geographical proximity is therefore not sufficient condition for knowledge transfer. Cognitive relatedness is another crucial factor for knowledge spillovers, learning and knowledge exchange (Boschma 2005). For each technology and production process there is a certain level of knowledge that is required in order to comprehend and implement them correctly. Cognitive proximity between two firms should be close enough to facilitate understating, communication and processing the new information.

Technological relatedness can thus be considered to be an important aspect steering the direction of knowledge spillovers, as the possibilities to diversify into new technologies and industrial sectors depend on existing portfolio of technological knowledge and expertise (Boschma, Balland & Kogler, 2015). The actual diversity of the technological knowledge base is an important indicator of future innovative potential for individuals, firms and regions (Kogler 2017) and a determinant of business opportunities leading to entry.

Innovation, market rivalry and appropriation

However, taking into account the high cost and importance of knowledge and innovation for competitiveness, incumbent firms will aim to shield their knowledge and increase appropriation, with the aim of deterring direct rivals and potential entrants (Belderbos & Somers 2015; Bloom et al. 2013).

Innovating incumbents may use various strategies to limit the extent of knowledge transfer to competitors or potential entrants (Levin et al. 1987). One possible way of increasing appropriation and reducing spillovers is the use of intellectual property rights, tools designed to increase innovators incentives in the efficient manner (Scotchmer 2004). Empirical research has been conducted mainly on patenting as strategies to protect the technological aspect of an innovation.

Marketing aspects are often neglected, which results in the implied assumption that commercial success is determined mainly by the technological features of innovation (Crass 2014). However, when spillovers lead to entry in the same product market, market rivalry will increase and margins erode. Branding is a key element for differentiation of firm's products from competitors and providing information about quality and "meaning" of its products (Belleflamme & Peitz 2010). Brands can be critical to the long-term success of an innovation as it can shield incumbents from increased competition in the product market and prevent the slide of the products into the commodity status, with related margin erosion (Aaker 2007). Trademarks provide a legal protection for the expenditure necessary to build the brand.

In the industrial organization literature loyalty to existing brands and reputation of incumbents are treated as important barriers to entry, and product differentiation or brand proliferation are seen as a form of entry-deterring strategies (Tirole 1988) (Lipczynski et al. 2005) (Belleflamme & Peitz 2010). Usage of trademarks or brands facilitates *"innovation appropriation"* and helps to associate innovations with the original innovating firm. The potential competitor or entrant, whose strategy is built on the imitation of the innovator, will not only have to master all the technical aspects of innovation but will have to overcome *"the power of brand"* (Aaker 2007) by advertising more than existing firms or by offering some other competitive advantages (Demsetz 1982). Trademarks may be thus used by incumbents to increase entry costs for new firms and act as entry deterrent. A strong brand and reputation may facilitate creation of a bottleneck capability necessary for impeding imitation (Kogut & Zander 1992) (Faria & Sofka 2008).

The role of brands or trademarks for appropriation of the innovation benefits is confirmed in several empirical studies modelled on the market value approach proposed by Griliches & others (1984). Bosworth & Rogers (2001) found a positive effect of higher trademark stocks on market value of firms representing non-manufacturing industries. Greenhalgh & Rogers (2006) found that higher R&D, EPO patenting and UK trade marking all tend to increase market value. While controlling for R&D and patents, Sandner & Block (2011) found that investors assign higher valuation to the firms with higher portfolio of trademarks and the number of oppositions filed by trademark owner against the registration of similar trademarks is positively related to firms' value. This finding confirms that investors value more firms that actively defend their marketing assets and underscores the importance of trademarks as an appropriation strategy.

Greenhalgh & Rogers (2012) look at the impact of competitors' trademarking on the individual firms' output and market valuation. The authors document a "market stealing" effect, stemming from the successful product launch of firm's immediate competitors, evidenced by a temporary loss in output. In contrast, the impact of industry trademarking activity on stock market value of firms is positive, reflecting investors' expectation that the losing firm will engage in innovation activity in the future, strengthening the Schumpeterian process of creative destruction. In the same line, Crass (2014) has shown that the use of established brands to promote innovation is associated with a 35% higher sales of innovative products. A study conducted by Office of Harmonization on Internal Market (OHIM 2015) showed that expected revenue per employee of trademark owners is almost 30% higher than the revenue of firms not registering trademarks.

In the economic literature, trademarks are, however, not only seen as an instrument of appropriability but also as an indicator of innovative output in its own right. The filing of new trademarks reflects the introduction of novel offerings on the market and an attempt to persuade consumers that this offering address their needs, not yet covered by existing products or services (Mendonca et al. 2004). Recent research found that trademarks appear to capture innovative activity not covered by other IPRs, such as innovation in small firms as well as low tech and service innovation (Flikkema et al. 2010) (Schautschick & Greenhalgh 2016). Innovative firms, that meet Community Innovation (CIS) criteria for innovativeness, consistently use more trademarks than non-innovative firms and use more trademarks than patents (Millot 2009).

There are strong theoretical arguments for ability of trademarks to complement and enhance patent protection (Rujas 1999)(Thoma 2015). While patent protection is limited to 20 years, trademarks may be renewed indefinitely and can reinforce the protection provided by patents by conferring extra market power to the innovator after his invention enters into the public domain (Rujas 1999). Llerena et al. (2013) showed that, depending on advertising spillovers and depreciation rates, trademarks and patents can be treated as complementary or substitute legal tools. Also Thoma (2015) confirmed positive effect of patent and trademark protection bundling within the same innovative project for valuation of patents on medical and cosmetic products.

The use of such strategic tools by incumbents may increase their appropriation, limit spillovers and, as a consequence, also reduce potential benefits stemming from agglomeration economies. Rosenthal & Strange (2003) indicate that employment in the same industry encourages entrepreneurs to set up in the given region but the strength of this relationship is moderated by the regional corporate organization and industrial structure. Employment at small establishments has more positive impact on entry than employment at medium and large companies; the latter seem better at appropriating their knowledge and use strategic tools to discourage entry and limit spillovers. Belderbos & Somers (2015) find supportive evidence that potential technological spillovers may be conditional on the incumbent´s strategic behavior. They showed that high concentration of technology activities among regional incumbent firms and strong degree of technology development internalization, including cross-border internalization, may discourage foreign R&D investors from setting up subsidiaries in the region.

Research questions

So far, the results of empirical research on the role of local knowledge stocks for firm entry has been mixed. The impact of regional knowledge stock on new firms formation was found either to be of minor importance or not confirmed at all (Jofre-Monseny et al. 2011) (Wong et al. 2005)(Knoben et al. 2011). One reason of the mixed empirical results may be that prior research has not taken into account that i) not all the knowledge is equally relevant for entrants; ii) that innovating incumbents may at the same time use strategies to appropriation the returns to innovation and therewith discourage entry. In the current study, we address these issues by distinguishing between local knowledge stocks in the focal industry and knowledge stocks in technologically related industries, and by taking into account trademark registrations of incumbents in the focal industry.

Our analysis starts from the notion that knowledge spillovers occur and constitute an important source of new entrepreneurial ideas. We examine this by focusing on local knowledge stocks (patents) as an important determinant of new firms formation, explaining entry patterns across regions and industries. The positive impact on the formation of new firms may be counterbalanced by the appropriation strategies of incumbents as reflected in trademark applications.

While innovation and spillovers are likely to create entrepreneurial opportunities for new entrants, patented inventions and the associated intellectual property rights are also part of firms' appropriation strategy that may limit the exploitation of technological opportunities by entrants (e.g. Leten, Belderbos, Van Looy, 2016). We may expect that incumbents will be more active in appropriating benefits of innovation in their core industries, and aim to limit spillovers and use their patent positions to challenge entry in these industries. This pattern will be less evident in case of entry in related industries, which does not directly affect the market positions of incumbents. Hence, our first research question:

Is the importance of incumbents' innovation (patenting activity) as positive determinant of entrepreneurial opportunities and new firm formation less in the incumbents' industry compared with technologically related industries?

Building strong brands protected by trademarks is an attractive strategy for incumbents, as efficient marketing is seen as one of the most important aspects of innovation success. The trademarks protecting brands in the incumbents' industry are likely to raise entry barriers for entrants in this industry. This may further limit the attraction of incumbent innovation and knowledge stocks to potential entrants in incumbent industries. Our second research question is:

To what extent does trademark activity by incumbents negatively moderate the relationship between incumbent innovation (patenting activity) and new firm formation in the incumbents' industries?

Data and sample

For our research design detailed geographic and industrial firm level data are required. Therefore, we base our analysis on ORBIS Bureau van Dijk dataset[1]. We use data on nearly 20 million firms with headquarter in one of 12 countries of the European Union (AT, BE, DE, DK, ES, FR, GB, HU, IT, LT, NL and PT). The main criterion for inclusion of firms from specific countries was the availability of data on national trademarks.

[1] April 2012 version

Although ORBIS dataset is the most complete source of micro data available, coverage and information details vary by country.

Previous comparisons indicated that there may be important differences between ORBIS and official statistics in terms of number of business records. Especially smaller firms may be underrepresented in some countries as they have to follow less stringent rules regarding financial data provision. Nevertheless after comprehensive checking and cleaning of data, it has become a standard data source for micro-data analysis at OECD (Ribeiro et al. 2010).

Different reporting regimes in different countries covered by our analysis may definitely have an impact on results focused on financial data, where the availability is scarce for some categories of firms and some countries. It is to lesser extent a problem for analyses using data on industry affiliation and establishment date. The coverage of these data in ORBIS is much higher, but nevertheless there are still differences in data availability between countries.

Concordance tables provided by Eurostat[2] were used to establish firms NUTS3 level on the basis of their postal codes available in ORBIS. NACE industry codes associated with firms in ORBIS are based on national registries. This information allows us to bring the data to our focal level of analysis: the various NACE 4 digit / NUTS3 combinations.

The knowledge stocks used in the analysis are constructed using patent data. There are many advantages related to usage of the patent statistics in innovation research and therefore patents are often used as a proxy for innovation. PATSTAT was the main source of the patent data. For the purpose of the study we have taken into account only national data available in PATSTAT.

TMView- information system on trademarks, created and maintained by EU IPO is the main source of the information on national trademarks and also the source we use for this analysis. The TMView dataset contains information about the current status of the national trademark (registered or expired). TMView data did not contain information on the applicants' address, so it had to be completed by the data provided by IP Offices of 12 countries represented in the dataset.

In merging the information from these different sources the following issues arose. There is no common key variable that could be used to link IP data with financial and demographic data of ORBIS. One variable that is present in both datasets is name and address of the firm. However, there are different conventions on how the same name and especially the same legal form could be written. Therefore, before actual matching, company names from ORBIS and the applicant's data from various IP registers have been standardized and harmonized extensively by capitalization, removal of the special characters and removal of the legal forms designations. In the harmonization of the names of the IPR owners, we followed steps developed by Magerman et al. (2006). However, we based our matching exercise on own lists of legal forms and weak words specific to the languages of countries represented by firms in our dataset. In general, the 'exact match' method has been employed. In case of ambiguous

[2] http://ec.europa.eu/eurostat/web/nuts/correspondence-tables/postcodes-and-nuts

match (several ORBIS records matched with one standardized IP record) various disambiguation procedures based on similarity of legal forms and geographical information (postal codes) were implemented. In few cases where this disambiguation procedure was not effective but all the ORBIS firms linked to the same IP record were part of the same economic group – confirmed by the link to the same Domestic Ultimate Owner (DUO)- the mother company of those firms was linked with IP records. A set of concordance tables between ORBIS and several IP registers was the final result of the matching exercise. Those tables contain unique identifiers of ORBIS (BvD id) and IP registers. Finally, TMView data did not contain information on the applicants' address. This had to be completed by the data provided by IP Offices of 12 countries represented in the dataset.

Measures and methods

New firm formation

The number of start-ups (new entries) in year t in NUTS 3-region in 4-digit NACE industry is the dependent variable in our models. New entrants are identified on the basis of the establishment date available at ORBIS. Firms with establishment date between 01/01/2001 and 31/12/2009[3] have been assigned a "start-up" status.

We are not able to distinguish between entrepreneurs starting new firms to pursue business opportunity from those who create firms out of necessity. However by limiting our sample to the manufacturing industries, which are characterized by the higher capital requirements, we reduce the likelihood of necessity entrepreneurship. Additionally, the longitudinal dataset enables us to control for time invariant aspects influencing entrepreneurial startups in given NUTS 3 regions / NACE4d industries. We use also a set of independent variables such as unemployment rate to control for time varying variables that may contribute to the necessity entrepreneurship. We also do not distinguish between de novo entrepreneurs and spin offs from incumbents.

Knowledge stocks

Our measure of knowledge stocks is based on patenting activity of firms. We considered all the applications, regardless of their final status- whether they were finally registered or not. This reflects the belief that even though the examination process finds that the innovative step was not significant enough to guarantee patent registration, its publication reveals all the details of the patent to public inspection. All interested parties may then familiarize themselves with the invention and spillovers of technical knowledge may occur. For all

[3] We initially used data of 2001-2012. However, a lower number of de novo firms in years 2010-2012 may be due to the economic crisis or may be the reduced availability of the ORBIS data. Since we cannot disentangle these two reasons, for the empirical models we limited the dataset only to years 2001-2009.

ORBIS firms for which we were able to match to the patent data we calculated the stock of patents starting with year 1900 using following the formula:

$$\mathrm{PS}_{trj} = \mathrm{PS}_{\mathrm{trj-1}} * 0.85 + \mathrm{P}_{trj} \tag{1}$$

Where: PS_{trj}- denotes patent stock in year t in NUTS3 region r and 4-digit NACE industry j; $\mathrm{PS}_{\mathrm{trj-1}}$- denotes patent stock in previous year; P_{trj}- stands for number of patents applied for in year t by firms located in NUTS3 region r and representing 4-digit industry j. The use of a 15% depreciation rate is a common in research on patents and R&D (Hall et al. 2005; Bloom et al. 2013;Lychagin et al. 2014;Belderbos & Somers 2015).

Trademark activity

We create trademark stock by aggregating trademarks that are still in force over incumbents representing 4 digit NACE industry and located in NUTS 3 regions. For each year of our analysis we update the stock by adding new registered trademarks and subtracting all trademarks that expire that year.

For the trademarks with status "expired" the exact expiration date was available only in case of UK, DE and HU. In those cases the number of trademarks forming part of the relevant trademark stock could be calculated on the basis of exact information of trademark validity. For all other countries we assumed that trademarks with status expired were valid for two protection periods (20 years)[4].

We allow for the possibility that, independently from being an innovation indicators, trademarks stocks may moderate the effects of technological knowledge stocks on entry. To empirically check the role of combining patents with trademarks' registration we construct an interaction term between the two (Jaccard & Turrisi 2003)(Jaccard & Jacoby 2010).

Technological relatedness of industries

As noted by Griliches (1979) most interesting knowledge spillovers are characterized by the ideas borrowed from one firm by others and which are not necessarily related to purchase of inputs. Seemingly unrelated industries that are not using each other's products as input to the production process may work on related technical problems and may use solutions invented in one field as the input to solving their own problems. In constructing relevant knowledge stocks for firm i in industry j we apply a distance measure relating firm i's industry with all other industries. This approach can be described by equation $\mathrm{K}_i = \sum_{\mathrm{j=1}}^{\mathrm{n}} \mathrm{w_{ij}} \mathrm{K_j}$ where $\mathrm{w_{ij}}$ is a weighting matrix representing a fraction of knowledge entering a production function of industry i borrowed from other industries. Weighting factors should become smaller as the "distance" between firm i's industry and j industry increases (Griliches 1992).

The most popular measure of technological similarity is Jaffe similarity index (Jaffe 1986). In its original form it describes similarity between firms taking into account proximity of the

[4] The mean validity period for Hungarian trademarks calculated on the basis of available data amounted to 15 years. The same period calculated for German trademarks amounted to 17 years and for British trademarks 19,5 years.

firms in the technological space. Bloom et al. (2013) provided the economic microfoundations for the Jaffe measure. In the traditional Jaffe notation, the similarity index is calculated in the following way:

$$TECH_{ij}^{J} = \frac{F_i F_j'}{(F_i F_i')^{1/2} (F_j F_j')^{1/2}} \qquad (2)$$

where F_i and F_j are the vectors of patent classes of firms i and j respectively. The measure allows for the calculation of the share of the respective International Patent Classification (IPC) subclasses vectors for two firms that point in the same direction in the highly dimensional IPC subclasses space.

Jaffe similarity index is bounded between 0 and 1, with value of 1 for firms' pairs that are characterized by the same patenting pattern and 0 for firms' pairs whose vectors are orthogonal.

We adapted the Jaffe similarity index to calculate technological similarity between NACE industries. For that purpose, information on 667 569 distinct European patent applications filed between May 1978 and September 2012 were used. Patent and trademark stocks in the technically related industries have been constructed by multiplying matrix of patent and trademark stocks aggregated for each year, NUTS3 region and NACE industry by the matrix of technological similarity of industries.

To account for the possibility that knowledge spillovers extend beyond the borders of NUTS3 regions we present the specification with weighted intellectual property variables. Our variables denoting knowledge stocks and trademarks' stocks in 50% consist of the variables related to focal NUTS 3 region and in 50% of the variables related to adjacent regions lying up to 200 km from the centroid of the focal NUTS 3 region. Intellectual property variables related to adjacent regions are weigthed with weights calculated on the basis of the inverse of geographical distance from focal NUTS3 region.

Control variables

Share of patents applied for by new entrants - As discussed by Winter (1984) technological regimes may have important influence on the propensity to start new firms. In the traditional view, technological regimes have been analyzed at the level of industry. However Audretsch & Fritsch (2002) have shown the existence of different geographical growth regimes, whereby high level of entry and exits occurs even in the industries with little or no innovative activity. Technological/regional regimes may thus influence the start-up rate irrespective of the level of innovativeness of the industry/regional unit. Therefore it is necessary to control for this aspect in our models. We introduce a control variable, the *share* of patent applications filed by young firms in a NUTS3 region, measured by the number of patent application of young firm over the total number of patent application in that NUTS3 region. We define a young firm as a firm which in the year of the patent filing is less than or exactly 5 years old (counting from the firm registration year). The variable is calculated for the whole period comprising years 2001-2009.

As explained in the literature section, agglomeration economies are one of the most important factors determining firm locations. It is important to control for agglomeration economies as omitting proxies for agglomeration may lead to overestimation of strength of the regional knowledge base (Knoben et al. 2011). Arauzo-Carod et al. (2010) provide an analysis of results of over 50 empirical papers on location choice models with a comprehensive review of variables used and their impact on location. In our empirical modelling we use some of these variables to account for agglomeration and localization economies, other than knowledge spillovers. Not all our control variables are available on the sufficient level of disaggregation and sometimes we have to use variables aggregated on the level of NUTS 2 regions.

Number of incumbents- As main control variable for agglomeration economies we use the number of incumbent firms active in focal NACE4d industry - focal NUTS 3 region. This variable has been calculated from ORBIS data by aggregating the number of firms registered into focal NACE4d and NUTS 3, with establishment year prior to year t or no establishment year available.

Population density - As a measure of urbanization, we use “Population density by NUTS 3 regions (inhabitants per square km)” retrieved from Eurostat table *demo_r_d3dens*[5]. A positive effect of this variable on new firm formation would indicate that more urbanized regions are more attractive for de novo entrepreneurs. In previous empirical studies the impact of population density on number of establishment was mixed (Arauzo-Carod et al. 2010).

Unemployment – Unemployment is available from Eurostat table *lfst_r_lfu3rt*- “Unemployment rates by sex, age and NUTS 2 regions (%)”[6] and based on the EU Labour Force Survey (EU-LFS). The unemployment rate shows unemployed persons as a percentage of the economically active population. In previous empirical studies impact of unemployment on number of establishment was mixed (Arauzo-Carod et al. 2010).

Educational attainment level- Educational attainment data are available from Eurostat table *edat_lfse_04* – “Population aged 25-64 by educational attainment level, sex and NUTS 2 regions (%)”. The table presents data on the highest level of education successfully completed by individuals of a given population. When determining the highest level, both general and vocational education is taken into consideration. The variable used in the models is ED3-8- *Upper secondary, post-secondary non-tertiary and tertiary education,*

[5] Table contains some missing data for some regions in some years. We have imputed missing data based on the NUTS 3 area and population data available in Eurostat.

[6] http://ec.europa.eu/eurostat/cache/metadata/en/reg_lmk_esms.htm

corresponding to the levels 3-8 of the International Standard Classification of Education (ISCED) 2011[7].

In previous empirical studies impact of education on number of establishments was mainly negative (Arauzo-Carod et al. 2010).

GDP per capita- We use this as a broad economic indicator of living standards. The data are taken from Eurostat table *nama_r_e3gdp* "Gross domestic product (GDP) at current market prices by NUTS 3 regions" and expressed in purchasing power standards (PPS) to eliminate differences in price levels between countries[8].

Growth of GDP capita- indicator for GDP growth has been calculated from our indicator of level of GDP per capita described above.

Blau diversity index- we use this variable to control for the diversity of industrial patterns on the NUTS3 level. The Blau index measures the spread of units across qualitatively different categories (Harrison & Klein 2007), with larger values representing a larger spread. Here the Blau index, based on Herfindahl- Hirschman index, is computed with the following formula:

$$1 - \sum_{i=1}^{k} p_i^2 \tag{3}$$

where p is the proportion of firms representing each NACE industry (on 1 digit aggregation) in overall number of manufacturing firms on NUTS3. The index ranges between zero (concentration) and one (spread), with a maximum value occuring when firms are spread equally between different industries on the local level. It can be also understood as a probability that two randomly selected firms belong to different NACE industries. In previous empirical studies the impact of sectorial diversity on number of establishment was mixed (Arauzo-Carod et al. 2010).

Table 1 shows the desciptive statistics for the variables. A correlation matrix of the variables used in the model is presented in Table 2.

[7] The availability of data for educational attainment varies depending on country. For example educational attainment data is not available for Danish regions before 2007. Until then only the aggregated country data was delivered to Eurostat by Danish authorities.

[8] http://ec.europa.eu/eurostat/statistics-explained/index.php/National_accounts_and_GDP

TABLE 1: DESCRIPTIVE STATISTICS FOR VARIABLES USED IN THE MODELS

DESCRIPTIVE STATISTICS

Statistic	**N**	**Mean**	**St. Dev.**	**Min**	**Max**
Number of startups in NACE4d and NUTS3	2,460,976	0.155	1.141	0	307
Number of incumbents in NACE4d and NUTS3	2,460,976	3.334	18.898	0	3,961
Patent stock in related industries (lag 1)	2,460,976	58.562	195.859	0	18,868.87
Patent stock in own industry (lag 1)	2,460,976	1.554	58.973	0	22,449.56
Trademark stocks in own industry (lag 1)	2,460,976	2.626	20.019	0	4,411.058
Unemployment level	2,460,976	7.675	4.099	1.2	26
GDP per capita in the region (PPS)	2,460,976	23,117.9	8,472.97	4,7	82,1
growth of GDP per capita in the region (PPS)	2,460,976	0.02	0.051	-0.27	0.41
Education level	2,460,976	71.83	14.824	16	97
Population density	2,460,976	533.6	1,089.107	6.9	21,242.6
Share of new firms in patenting activity	2,460,976	0.017	0.12	0	1
Blau index	2,460,976	0.874	0.063	0	0.938

TABLE 2: CORRELATION MATRIX FOR VARIABLES USED IN THE MODELS

		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
1	Number of startups in NACE4d and NUTS 3											
2	Number of incumbents in NACE4d and NUTS 3	0.38										
3	Patent stock in related industries (lag 1)	0.05	0.21									
4	Patent stock in own industry (lag 1)	0.12	0.39	0.34								
5	Trademark stock in own industry (lag 1)	0.24	0.58	0.20	0.50							
6	Unemployment level	-0.01	-0.05	-0.33	-0.09	-0.06						
7	GDP per capita in the region (PPS)	0.03	0.10	0.49	0.13	0.11	-0.37					
8	Growth of GDP per capita in the region (PPS)	0.00	-0.02	-0.07	-0.02	-0.03	0.04	-0.03				
9	Education level	-0.07	-0.13	0.38	0.07	-0.19	-0.04	0.09	0.00			
10	Population density	0.04	0.10	0.37	0.09	0.02	-0.14	0.50	-0.05	0.16		
11	Share of new firms in patenting activity	0.10	0.22	0.10	0.23	0.17	-0.03	0.05	-0.01	-0.02	0.04	
12	Blau index	0.03	0.09	0.14	0.02	0.02	-0.09	0.04	0.12	0.02	0.21	0.03

Models specification

The dependent variable (number of firms entering the market in year t) is a count variable that takes only non-negative integer values. In cases of modelling such data, linear regression modelling is inadequate (Cameron & Trivedi 2005;Kennedy 2008;Wooldridge 2010). The proper modelling approach for count variables is based on a Poisson distribution, which is parametrized in terms of a single parameter (μ) and all moments of function y are a function of only this parameter (Cameron & Trivedi 2005). The Poisson distribution assumes equidispersion- equality of mean and variance.

However, our data are characterised by a large overdispersion. Whereas the mean number of startups is 0.16, its variance amounts to 1.36. The consequences of overdispersion in this case are comparable to the failure of the assumption of homoscedasticity in the linear regression model (Cameron & Trivedi 2005). Whereas the coefficients of the model are consistent, standard errors are grossly deflated. As a result, t-statistics are inflated and may lead to the false statistical significance conclusions. Similarly, an underestimation of the frequency of zeros results in estimates that are inconsistent. Overdispersion and an excess of zero observations are the result of unobserved heterogeneity in the conditional mean parameter (Mullahy 1997).

In many empirical applications focused on the location of new firms, the equidispersion assumption is too restrictive (Arauzo-Carod et al. 2010). The adequate strategy in such circumstances is to account for the bias in the standard errors by using robust or clustered standard errors. We apply robust variance adjustments to the data to reflect the fact that observations are not independent. Modified variance estimators allow for inference that is robust to within regions correlation, but at the same time assumes that NUTS3 regions are independent from each other, which in the case of spatial data is not necessary the case. Poisson regression with empirical standard errors is often used adjustment for extra-dispersion, or any other type of excess correlation within data (Hilbe 2014).

A fixed effect specification is a very interesting option for econometric modelling of panel data as it allows to control for unobserved variables that are fixed over the analysed period. The basic unit of observation of our dependent variable is the NUTS3 region- NACE 4-digit industry. However, for many such combinations we observe zero entries with no existing incumbents. Also, the presence of certain NACE 4-digit industry in a certain NUTS3 region is only a theoretical possibility. We also may observe entries into new industries, not previously present in the region. Therefore, using of the unconditional fixed effects specification for our models is not adequate. Instead we control for NUTS3 region, NACE 2 digit level and years fixed effects by using dummy variables, conditioning the fixed effects out of our models (Allison 2009).

TABLE 3 RESULTS OF THE POISSON REGRESSION MODELS

Dependent variable: number of new firms in nace4d/NUTS3	(1)	(2)	(3)
log of patent stock in related industries (lag 1)	0.186***	0.186***	0.173***
	(0.012)	(0.012)	(0.012)
log of patent stock in own industry (lag 1)	-0.056***	-0.062***	0.035***
	(0.007)	(0.008)	(0.012)
log of trademark stocks in own industry (lag 1)		0.011	0.028***
		(0.008)	(0.009)
interaction between patent and trademarks stocks (own industry)			-0.036***
			(0.005)
share of new firms in patenting activity	0.251***	0.252***	0.230***
	(0.019)	(0.020)	(0.019)
log of incumbents' number (NACE/NUTS)	1.084***	1.080***	1.075***
	(0.006)	(0.007)	(0.008)
log of population density	-0.493**	-0.499**	-0.442**
	(0.195)	(0.196)	(0.189)
unemployment level	-0.005	-0.005	-0.005
	(0.003)	(0.003)	(0.003)
% of inhabitants with secondary and tertiary education	-0.010***	-0.010***	-0.009***
	(0.003)	(0.003)	(0.003)
log of GDP per capita in the region (PPS)	-0.086	-0.090	-0.099
	(0.095)	(0.096)	(0.097)
GDP per capita growth in the region (PPS)	1.037***	1.035***	1.048***
	(0.109)	(0.109)	(0.109)
Blau index	-0.660***	-0.659***	-0.629***
	(0.167)	(0.168)	(0.170)
Constant	-1.416	-1.364	-1.538
	(1.347)	(1.353)	(1.358)
Regional (NUTS 3) fixed effects	Yes	Yes	Yes
Industry (NACE 2) fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	2,460,976	2,460,976	2,460,976
Akaike Inf. Crit.	1,242,177	1,242,157	1,241,218
Note:	**p<0.05; ***p<0.01		

Results

Results of the estimations are presented in Table 3. The first column shows a model with focal variables for patent stocks, in own and related industry (model 1). To that model, are added the trademark stocks in own industry (model 2) and the interactions of patent and trademark stocks in own industry (model 3).

As shown in the table, agglomeration economies proxied by the number of incumbents within focal NACE4d industry NUTS3 region have strong positive effect of the number of firms entering the market. The coefficient of this variable is positive and larger than 1, which, ceteris paribus, implies that an increase in the number of incumbents leads to a more than proportional increase in the number of entrants within the same NACE4d/NUTS3.

As expected, the type of technological regime in the region and industry, proxied by the share of young firms in the patenting activity, has a strong impact on entry. A ten percent growth of the share of young firms in patenting activity leads to 2.3 percent rise of the number of entries.

Neither unemployment level nor the level of GDP per capita as such have a significant impact on entry. GDP growth, by contrast, is a factor with strong, positive impact.

Surprisingly, other factors often related to localization advantage such as the level of education and population density are associated with lower firm formation and the relevant results are statistically significant.

Diversity of the industrial pattern within a region is, however, negatively associated with new firms' emergence.

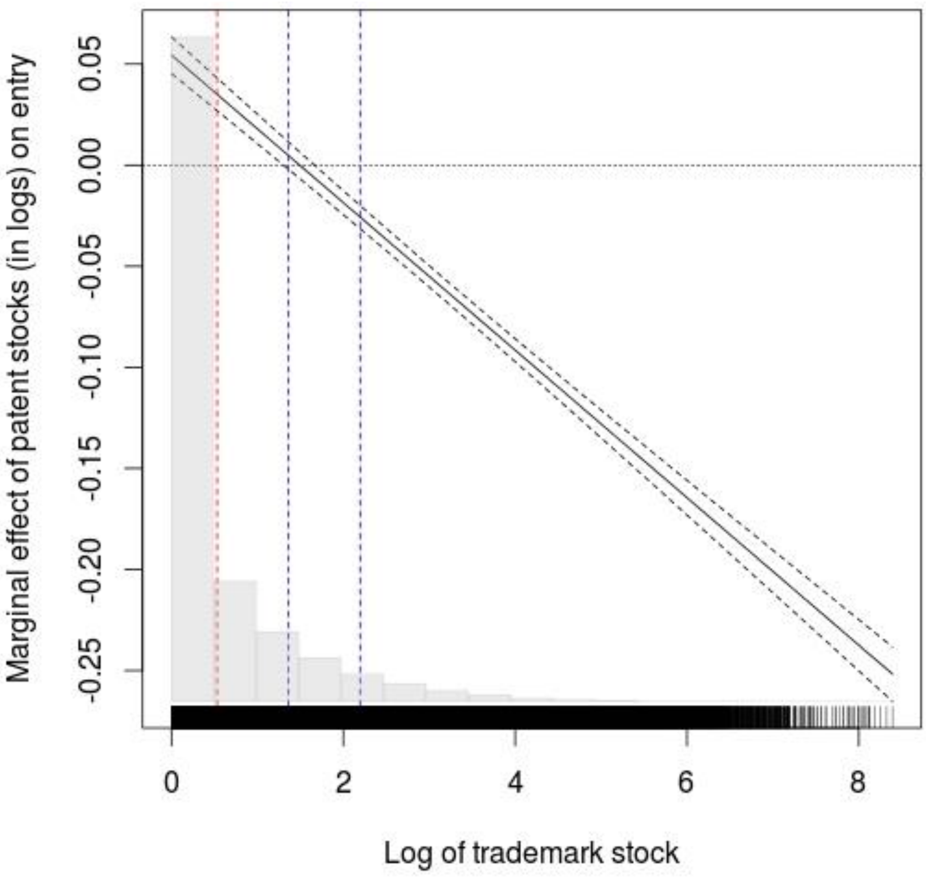
Results in model 1 show that higher knowledge stock in related industries have a positive impact on entry, and higher knowledge stock in the narrow NACE4d industry is negatively associated with entry.

Adding own trademark stocks variables in model 2 does not radically change the picture. The coefficient of the knowledge stocks in related industries remains positive and statistically significant and its magnitude is the same as in the model not controlling for own trademark stocks. The coefficient of the knowledge stocks in the own industry remains negative and its magnitude barely differs from the model not controlling for trademarks (model 1). Interestingly the coefficient for trademarks stocks in own industry is not statistically significant even on 95% confidence level.

Model 2 depicts impact of knowledge stocks at each level of all the other predictor variables present in the model, including different levels of trademarks' stocks. Model 3 reveals that appropriation strategy of incumbents' is crucial for the strength of knowledge spillovers within narrow NACE industry at the local level. When the variable of interaction between patents and trademarks is added into the model, coefficient of the related knowledge stock remains positive and implies that 10% increase of the patent stock results in 1.7% higher entry at each level of other variables included in the model. However, coefficients of both knowledge and trademarks' stocks for own industry become positive and statistically significant. As we added an interaction term between own patent applications stock and trademarks stocks and we mean centered values of patent applications' stock and trademark stock variables, coefficient of the own industry patent stock represents conditional impact of patent applications stock increase at mean level of trademark stock.

Coefficient of interaction variable confirms that impact of patent applications stock on entry is moderated by trademark stocks of incumbents. As shown in Figure 1, at zero trademark stock, 10 percent increase of the patent stock leads to 0.54 percent increase in entry. At mean value of log transformed trademark stock (corresponding to roughly 1.7 trademarks), 10 percent increase of patent stock leads to 0.35 percent increase of entry in the same industry. However, impact of increase in the patent applications stock becomes negligible for entry in the own industry at the local level, at approximately one standard deviation from the mean value of log transformed trademark stock, which corresponds to approximately 4.5 trademarks. At higher values of trademark stocks kept by incumbents, increase in patent stocks leads to lower entry.

FIGURE 1 RELATIONSHIP BETWEEN PATENT STOCKS AND ENTRY FOR DIFFERENT LEVELS OF TRADEMARK STOCKS



*Note: red dashed line corresponds to mean value of log transformed stock of trademarks, blue lines correspond to mean+ standard deviation and mean + 2*standard deviation value of log transformed stock of trademarks*

Discussion and concluding remarks

The present paper adds to the literature focusing on impact of regional knowledge stocks on entry, by analyzing two important aspects that may be crucial for the strength and direction of knowledge spillovers: technological relatedness between incumbents and potential recipients of knowledge externalities and the impact of strategic means of appropriation at the disposal of incumbents

The main finding from this paper is that the strength of knowledge spillovers from incumbents' innovation depends on the degree of market rivalry and technological relatedness between incumbent and potential recipient. Positive impacts of increases in the knowledge stocks in the focal industry appear to be counterbalanced by strengthening of the competitive position of incumbents, deterring entry in that same industry. Therefore it is rather innovation from incumbents active on different markets, but using similar technologies, that provides new entrepreneurial opportunities explored by new firms in the close geographical vicinity. Higher impact of innovation of incumbents from related industries, seems to validate Jacobs' hypothesis. However as evidenced by our results, mere diversity of local industrial patterns have negative impact on entry. It seems therefore that the main chanel diversity impacts entry is through knowledge spillovers between different industries. For that to operate, there must be some degree of shared technological competences between innovating incumbent and entrant, as claimed by MAR.

Knowledge spillovers from technological innovations may be further limited by more active appropriation strategies of incumbents. By combining technological innovations with investments in brands and marketing efforts, incumbents are able to appropriate more benefits from their innovations and shield their knowledge from entrants active in the same industry.

Knowledge spillovers seem to be affected by the nature of technological regimes in the focal region. A more active role played by young firms in local knowledge creation efforts encourages entrepreneurs to set up the business. Young firms focused on innovation and struggling to expand rapidly their market share are less concerned about shielding their knowledge from prospective entrants. Higher share of young firms in patenting may also indicate that search for a dominant design is not yet concluded and new firms may still succeed with their value proposition. It confirms observation of Bhide (2003) that higher uncertainty, stemming for instance from technological changes, help entrepreneurs with limited endowments to start their business.

Present study suffers from some limitations. Our interaction variable (product of knowledge and trademarks stock) is based on the data aggregated on the NACE4d/NUTS3 level of industries and regions. We are not observing an actual bundling of patents and trademarks on the level of individual innovation or even individual firm. It would be interesting to verify our findings with the more granular data on bundling strategy.

Spatial data samples, such as ours, require proper handling of the spatial dependence between the observations. There are alternative estimations procedures to deal with this problem developed under the classical spatial econometrics literature, however they are not suited for count data (LeSage 1999). We partially dealt with spatial dependence by weighting and aggregating knowledge and trademarks stocks for the regions lying within 200 km radius from the focal NUTS 3 centroids. However it is likely that some spatial correlation still remains in the standard errors of our model. There are several alternative estimation techniques considered for count data that could be used in the future to deal with spatial correlation, with most promising approaches based on Bayesian setting (Simões & Natário 2016).

Annex:

TABLE 4 TOP 20 MANUFACTURING INDUSTRIES WITH HIGHEST NUMBER OF ENTRIES BETWEEN 2001 AND 2009

	NACE	ENTRIES	NACE DESCRIPTION	DIVISION
1	2562	21,562	Machining	Manufacture of fabricated metal products, except machinery and equipment
2	1071	21,347	Manufacture of bread; manufacture of fresh pastry goods and cakes	Manufacture of food products
3	1812	18,245	Other printing	Printing and reproduction of recorded media
4	2511	15,880	Manufacture of metal structures and parts of structures	Manufacture of fabricated metal products, except machinery and equipment
5	3109	13,770	Manufacture of other furniture	Manufacture of furniture
6	2512	12,737	Manufacture of doors and windows of metal	Manufacture of fabricated metal products, except machinery and equipment
7	3299	11,499	Other manufacturing n.e.c.	Other manufacturing
8	1623	10,309	Manufacture of other builders' carpentry and joinery	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
9	1413	9,988	Manufacture of other outerwear	Manufacture of wearing apparel
10	3312	9,224	Repair of machinery	Repair and installation of machinery and equipment
11	2599	8,559	Manufacture of other fabricated metal products n.e.c.	Manufacture of fabricated metal products, except machinery and equipment
12	1813	8,429	Pre-press and pre-media services	Printing and reproduction of recorded media
13	3250	8,100	Manufacture of medical and dental instruments and supplies	Other manufacturing
14	3320	6,975	Installation of industrial machinery and equipment	Repair and installation of machinery and equipment
15	2229	5,739	Manufacture of other plastic products	Manufacture of rubber and plastic products
16	3101	5,585	Manufacture of office and shop furniture	Manufacture of furniture
17	1629	5,174	Manufacture of other products of wood; manufacture of articles of cork, straw and plaiting materials	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
18	2829	5,099	Manufacture of other general-purpose machinery n.e.c.	Manufacture of machinery and equipment n.e.c.
19	1419	5,075	Manufacture of other wearing apparel and accessories	Manufacture of wearing apparel
20	1520	5,040	Manufacture of footwear	Manufacture of leather and related products

TABLE 5 TOP 20 NUTS 3 REGIONS WITH HIGHEST NUMBER OF MANUFACTURING FIRMS ENTRIES BETWEEN 2001 AND 2009

	NUTS_3	Region name	Number of entering firms
1	ES511	Barcelona	10,785
2	ES300	Madrid	7,360
3	PT11A	Área Metropolitana do Porto	5,103
4	HU101	Budapest	4,860
5	ITC4C	Milano	4,821
6	ES521	Alicante / Alacant	4,530
7	ES523	Valencia / València	4,066
8	ITF33	Napoli	3,559
9	NL339	Groot-Rijnmond	3,465
10	ITI43	Roma	3,416
11	HU102	Pest	2,803
12	NL326	Groot-Amsterdam	2,691
13	FR101	Paris	2,620
14	PT170	Área Metropolitana de Lisboa	2,606
15	NL310	Utrecht	2,545
16	ES618	Sevilla	2,536
17	ES620	Murcia	2,406
18	ITC47	Brescia	2,307
19	ITC11	Torino	2,229
20	NL414	Zuidoost-Noord-Brabant	2,225

TABLE 6 TOP 20 NUTS 3 REGIONS WITH HIGHEST PATENT STOCKS IN 2009

	NUTS_3	Description	Aggregated stock of patents
1	DE212	München, Kreisfreie Stadt	28,324
2	DE115	Ludwigsburg	21,590
3	FR105	Hauts-de-Seine	13,036
4	DE111	Stuttgart, Stadtkreis	8,666
5	DE21H	München, Landkreis	5,745
6	FR103	Yvelines	5,364
7	DE913	Wolfsburg, Kreisfreie Stadt	4,674
8	DE147	Bodenseekreis	3,960
9	FR101	Paris	3,301
10	UKI32	Westminster	2,999
11	DEA24	Leverkusen, Kreisfreie Stadt	2,806
12	DE211	Ingolstadt, Kreisfreie Stadt	2,422
13	ITC4C	Milano	2,241
14	DE11D	Ostalbkreis	1,806
15	DE113	Esslingen	1,738
16	FR623	Haute-Garonne	1,617
17	DE600	Hamburg	1,599
18	DE300	Berlin	1,590
19	DEA1C	Mettmann	1,586
20	UKI31	Camden and City of London	1,551

TABLE 7 TOP 20 NUTS 3 REGIONS WITH HIGHEST TRADEMARKS STOCKS IN 2009

	NUTS_3	Description	Trademark stocks
1	ES511	Barcelona	27,236.730
2	ITC4C	Milano	19,056.670
3	ES300	Madrid	13,631.500
4	FR101	Paris	11,470.120
5	FR105	Hauts-de-Seine	10,248.430
6	ES523	Valencia / València	7,402.333
7	ITC11	Torino	5,936
8	ITI43	Roma	5,336.500
9	PT11A	Área Metropolitana do Porto	5,201
10	PT170	Área Metropolitana de Lisboa	4,606
11	ITH34	Treviso	4,307.583
12	FR716	Rhône	3,923.500
13	ITH55	Bologna	3,771.500
14	ITH32	Vicenza	3,692.833
15	ITI14	Firenze	3,533
16	ES521	Alicante / Alacant	3,452.500
17	ITC47	Brescia	3,449.250
18	ES620	Murcia	3,311.500
19	ITC46	Bergamo	3,203
20	ES213	Bizkaia	3,162.500

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