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The Role of Technology and Relatedness in Regional Trademark Activity

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Abstract

This paper provides insights on trademark activity at the regional level via two objectives. First, it examines the relationship between technological capabilities and new trademark applications. Second, it examines whether regions branch out to new trademark specializations that are related to their existing specializations. We employ EUIPO's data to study 218 European NUTS-2 regions (16 countries) over the period 2000-2016. Results show that increased technological stock is associated with more trademark applications and that existing trademark relatedness induces new specializations. These findings contribute to better understanding of trademark activity and policies related to regional diversification including Smart Specialization.

Keywords: Technological capabilities, Marketing activities, Trademark applications, Regional diversification, Relatedness, EUIPO.

JEL: O34, O38, R11

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1. Introduction

Firms continuously invest in innovative and marketing activities to either create or add value to their products and services. Such activities in turn create brand awareness for the firm differentiating it from its competitors. This awareness becomes an intangible asset referred to as brand equity resulting in the firm's increased profitability and protagonist role in the marketplace (Keller 1993; Simon *et al.* 1993).

Popular news outlets, such as Forbes, place several firms' brand equity value in the tens of billions USD or even in the hundreds for the likes of Apple, Google and Microsoft. The value of building brand equity however is not located just in multinational enterprises or conglomerates; it is also important for Small and Medium Enterprises (SMEs). In their recent study Crass *et al.* (2019) estimated the median European firm's brand equity value in the hundreds of thousand Euros. Given this importance of brand equity, firms that wish to invest in innovative and marketing activities need an instrument that would protect its intangible nature.

Trademarks fill this protective role by providing firms with rights over attributes that differentiate their products and services (Hall *et al.* 2014). They can protect a wide array of differentiating elements including words, phrases, symbols or combinations thereof (von Graevenitz 2013). As a result, trademarks are used by small and big firms alike (Rogers et al., 2006; Seip et al., 2019) and across multiple industries including the service sectors (WIPO 2013; Castaldi 2018).

Given this important role of trademarks and their overwhelming use, scholars have examined them in detail. They have shown that trademarks are positively associated with a multitude of firm outcomes including market value (Sandner and Block 2011), employment growth (Link and Scott 2012), firm survival (Giarratana and Fosfuri 2007) and attracting venture capital (Block *et al.* 2014).[1] A recent regional-level analysis has also shown that trademark activity is associated with higher likelihood of a region's economy to be more resilient during an economic crisis (Filippetti et al., 2019).

With these findings under consideration it is not surprising that there is a significant policy and academic interest on trademark activity. At the firm-level the most significant line of research is the one that aims to link trademarks with firms' technological advancements (Seip et al., 2018; Bei 2019). The intuition is that trademarks serve as a protection mechanism of marketing and

[1] For comprehensive reviews see Schautschick and Greenhalgh (2016) and Castaldi (2020).

commercialization activities promoting new and improved technologies. When we dwell deeper into trademark activity an additional important aspect is how firms will diversify in new trademark activities (Semadeni 2006; Gao and Hitt 2012), as recent studies have shown this sort of diversification can be significant for firm value (Castaldi and Giarratana 2018; Hsu *et al.* 2019). However, at the regional level we know little on how technological capabilities relate to trademark activity or how the diversification process takes place.

To this end, the objective of the paper is twofold. First, it examines whether technological capabilities, approximated by patenting activity, are associated with follow-on trademark activity in the region. Second, it provides insights on how the region's pre-existing trademark specializations can influence new trademark specializations. In other words, it will analyze the role of trademarks' relatedness in regional diversification.

Our first source of information is the European Union Intellectual Property Office (EUIPO) where we collect the population of all trademark applications filed at the office during 2000-2016. We observe detailed annual trademark activity for 16 EU countries over 218 NUTS-2 regions during this time period. In addition, we collect the patent application counts filed at the European Patent Office (EPO) during the same time period from the OECD REGPAT database.

To examine the first objective, we provide a panel data analysis where we regress a region's annual trademark applications on a region's patent stock. Results show that trademark activity is closely linked with technological activity in a region. This finding provides significant support to prior studies that associated trademarks with innovative activity (Schmoch 2003; Mendonça *et al.* 2004; Millot 2009). [2] We contribute to this line of work by extending it at the regional level by showing that technological capabilities are followed by trademark activity suggesting that the latter function as a protection mechanism for marketing activities that commercialize technological advancements.

Two additional facts regarding EUIPO trademark applications should be noted. First, EUIPO's trademark applications are registered only after they have proven actual sales thereby directly relating to commercial activities. Second, a trademark registered at this office has EU-wide coverage implying an export orientation. Combining these facts with our empirical findings

[2] The EU Innovation Scoreboard has also recently employed trademark counts in the compilation of innovation rankings (European Commission, 2015).

highlight the importance of EUIPO-related trademark activity in capturing marketing and business activity of technological advancements at the regional level.

Recognizing this significance of trademarks, the second objective of the paper aims to examine the process of new trademark specializations. The paper builds on the literature's methodologies starting with Hausman and Klinger (2007) and Hidalgo *et al.* (2007). However, instead of using industry classifications we employ the Nice classification system pertaining to trademarks. We find that regions will branch out to new trademark classes that are closely related to its existing trademark capabilities.

These findings relate to the economic geography literature that examines how regions can exploit their existing competencies to specialize into new business opportunities; in other words, how relatedness influences regional diversification. In the EU the importance of this process can translate to the concept of Smart Specialization. The Smart Specialization concept originally emanated from the Knowledge for Growth expert group (Foray and van Ark 2007; Foray *et al.*, 2009). The premise of this concept is to prioritize industries or technological fields where entrepreneurs can branch out to new value-adding specializations. The Smart Specialization Strategy calls for regional policy to enhance this process by supporting the product/service areas where regions are more likely to exhibit new specializations (Foray *et al.*, 2011). Policy makers within the EU quickly embraced the concept as early as 2013. Indeed, both the EU 2020 Innovation Plan and the EU Cohesion Policy encompass in key dimensions the Smart Specialization concept (Crescenzi *et al.* 2018)

However, in its early years, this concept lacked the appropriate theoretical underpinnings and empirical validation. Scholars since then have elaborated significantly on this concept for regional growth (Foray *et al.* 2011, 2012; McCann and Ortega-Argilés 2015). In addition, a growing literature has empirically quantified the role of relatedness in regional diversification providing insights on the policy aspect of Smart Specialization.[3] These previous studies have examined new specializations by estimating diversification in various dimensions, including labor, exports, and technology approximated by patents. However, as we show in the first objective of the paper, trademark activity is able of capture the business-related endeavors of technological activities. Therefore, how such endeavors diversify at the region over time is a timely issue of policy.

[3] For literature reviews see Boschma (2017) and Kogler (2017).

2. Technology, Relatedness and Trademark Activity

2.1. Technological Capabilities and Trademark Activity

The early empirical studies on trademarks aimed to examine their use in the context of firm strategy. These studies showed that trademarks can function as a protection mechanism for value-added marketing activities promoting new innovative products and services (Schmoch 2003; Mendonça *et al.* 2004; Millot 2009). Many follow-up studies provided insights by outlining the interplay between patents and trademarks. Llerena and Millot (2020) showed that the degree of complementarity depends on the specific industry. Zhou *et al.*, (2016) showed that trademarks and patents can function in a complementary fashion for firms seeking external financing in the form of venture capital. Dosso and Vezzani (2019) and Thoma (2020) reached to similar conclusion regarding the complementarity of patents and trademarks when examining firm and patent value respectively. Finally, Flikkema *et al.*, (2019) provided a detailed analysis of which types of trademarks may relate more to product and service innovation.

The overall intuition behind this strong relationship between patents and trademarks at the firm-level is that trademarks may function as a protection mechanism for the commercialization activities of technological innovations. However, at the regional level this relationship does not need to hold as the population of trademarks may not be as closely linked to overall technological capabilities. There are several potential reasons why this may be true.

Trademarks can capture inventions that are commercialized whereas patents capture the population of inventions (Nam and Barnett 2011; Castaldi and Dosso 2018). What is more, trademarks may also capture new products and services that could not be patented due to subject matter.[4] Further, given the relatively low standards and fees of obtaining trademarks, firms with budget constraints may pursue trademark protection while relinquishing patent protection. For instance, Fink *et al.*, (2018) showed that in Chile domestic firms will primarily employ trademark protection for new product introductions. Finally, in a region firms may pursue marketing activities without relying directly or indirectly on the region's technological advancements.

The above reasons could blur the strong relationship between patents and trademarks that few firms may exhibit. Nonetheless, it could also be the case that the technological activity in a region

[4] A patent needs to satisfy four criteria for patentability one of which is subject matter (Ouellette 2015). For instance, business method inventions are generally not patentable in most patent offices (Beresford 2000).

will spur marketing activities to commercialize on these advancements. To test which argument is more prevalent we formulate the following Hypothesis:

Hypothesis 1: A region with increased technological capabilities will generate more trademark applications.

2.2. Regional Diversification in Trademark Activities

Three general theories of regional economic growth have occupied the bulk of scholarly and policy interest. Marshall's theory (1890) with the additions of Arrow (1962) and Romer (1986), noted as MAR, focus on a single industry and examine how firms within an industry will benefit from formal and informal interactions. MAR therefore calls for specialization in a region as a driver of economic growth. On the other hand, Jacobs (1969) posits that economic diversity in a region will result to positive externalities by amplifying knowledge spillovers that in turn can promote economic growth. Finally, Porter (1990) argued that competition is an important driver by weeding out inefficient firms and pushing efficient firms to pursue more innovation. The three theories warrant for different industry compositions within a region. MAR posits for specialization; Porter (1990), while similarly argues for industry specialization, posits that intense competition is the key driver. Jacobs however argues that diversity will favor the conditions for growth.

Early seminal studies provided empirical validation for Jacobs (Glaeser *et al.* 1992; Feldman and Audretsch 1999). Follow-up studies however found support for either of the three theories. De Groot *et al.*, (2016) conducted a meta-analysis of these studies. They showed that it could be either specialization, diversity or competition that promotes economic growth. Which of the three is likely to be the driver depends on the sectoral, spatial and temporal characteristics that each analysis considers. The conclusion from this meta-analysis was that heterogeneity plays a key role in the process of economic growth for each region.

Dwelling deeper on the concept of industrial composition within a region, Frenken *et al.* (2007) formulated the types of industrial variety within a region. They posited that related industrial sectors will be more likely to exhibit Jacobs externalities than unrelated industrial sectors. They found that related variety is a driver of employment growth. Employment growth can occur because related industries are more likely to share knowledge, exploit economies of scope and spawn in new related activities (Content and Frenken 2016; Boschma 2017). This latter process can be viewed as a branching process, where new specializations are generated from related industries.

Hidalgo *et al.*, (2007) were the first that examined this branching process at the country-level. They investigated how a country gains a comparative advantage, or in other words specialize, in a new product. They found that a country is more likely to gain a comparative advantage (specialize) in products that are closely related with products that it already possesses such advantage.

Following-up on this finding, scholars in economic geography have shown that this strong relationship of relatedness in new specializations applies to smaller regions and extends beyond trade activity. Starting with Neffke *et al.*, (2011), researchers have elaborated on this relationship across many settings (Boschma et al., 2013; Essletzbichler 2015; Rigby 2015; Petralia *et al.*, 2017; Balland et al., 2019).

In our setting we should expect a similar relationship; that is, a region will exhibit a new specialization in a trademark class that is closely related to trademark classes that the region already possesses specializations. Hence, the second Hypothesis can be stated as:

Hypothesis 2: A region is more likely to develop a new trademark specialization in a class that is related to its existing trademark specializations.

3. Data and Variables Construction

3.1. Data Construction and Configuration for Testing Hypothesis 1

The data on the population of trademark application records were collected from EUIPO.[5,6] The following information for each trademark application was obtained: the application date, the applicant identifier and the Nice classification(s) the trademark is associated with. Overall, we collected information on 1,244,339 trademark applications filed during 2000-2016.

An important aspect of trademarks is their Nice classification. When applicants file for a trademark application they should also claim the Nice classifications their trademark can be used.

[5] In the European Union (EU), the Office for Harmonisation in the Internal Market (OHIM) was founded in 1994 with purpose of accepting and registering, after due examination, trademark applications (Council Regulation (EC) No 40/94). In 2016, OHIM changed its name to European Union Intellectual Property Office (EUIPO).
[6] https://euipo.europa.eu/ohimportal/en/open-data

The Nice classification scheme categorizes the entire business spectrum in 45 distinct classes.[7] For an applicant to register the trademark in a particular Nice class, she needs to show that she is using it commercially in the specific class. Therefore, the trademark should be associated with actual business activity in each of these Nice classes. Figure A1 of Web Appendix displays the frequency of Nice classes over the population of trademarks.[8] The most populous classes are 9 which relate to various electronic products and 35 which pertain to business- and advertising- related services. Table A1 of Web Appendix outlines the description of each Nice class. It is also useful to discuss the distribution of trademark applications by country of applicant. After dropping approximately 12% of trademark applications that lacked applicant's country information, the distribution by country over 2000-2016 is displayed in Table A2. US and Germany compete for the first place with 173,873 and 175,892 applications respectively. Intuitively, many European countries are frequent users of EUIPO including United Kingdom, Italy, Spain, France, Netherlands and Sweden. In the top 20 countries, which account for 89% of trademark applications, in addition to US the rest of the non-European countries are Japan, China and Canada. For the most recent overview of the trademark landscape from EUIPO data see also Mendonça (2014).

Our focus in this paper is on the EU NUTS-2 regions. Note that the 28 EU countries, as of 2016, accounted for 69% of EUIPO's trademark applications during 2000-2016. We first drop four single-region EU countries (EE, LI, LU and LV) as in Xiao *et al.* (2018), as for these member-states there would be no within country variation.

To match trademark applications to NUTS-2 regions, we downloaded European Commission's NUTS2-postal codes concordance.[9] With the help of the latter data, and an elaborate geocoding, we attempted to assign each trademark application to a NUTS-2 region. However, for several trademark applications such assignment was not feasible either due to typos, different format in postal codes between databases or postal codes that were no longer used. To ensure that each country's NUTS-2 regional trademark activity was adequately observed, we kept in the sample countries only if more than 90% of its trademark applications were assigned to its NUTS-2 regions. Unfortunately, the matching of eight countries was below the 90% threshold. These were: Belgium, Bulgaria, Croatia, Cyprus, Greece, Ireland, Malta and Romania. With these

[7] http://www.wipo.int/classifications/nice/en/

[8] If a trademark claims more than one class, then we double count it. The qualitative nature of the Figure does not change if we weigh trademarks based on the Nice classes they claim.

[9] https://ec.europa.eu/eurostat/web/gisco/geodata/reference-data/administrative-units-statistical-units/nuts

restrictions under consideration the analysis takes place for 218 NUTS-2 regions over 16 countries; overall, for these countries 95% of all trademark applications were matched to their NUTS-2 regions. Finally note that these 16 countries account for 92% of trademark activity within the EU for the period studied.

Further, we supplement these data with annual count of patent applications by NUTS-2 region. This information is collected by the OECD REGPAT database (Maraut *et al.*, 2008). We opted for applications filed at the European Patent Office (EPO) as this office is the closest counterpart to the EUIPO.[10] These data have been employed in multiple economic geography papers including regional diversification studies (Balland et al., 2019; Santoalha 2019). To construct the patent stock by region, $PatentStock$, we use these annual patent filing counts and employ the perpetual inventory method using a 20% depreciation rate (Guellec and Van Pottelsberghe de la Potterie 2004). Finally, population, GDP and area data by regions, were downloaded from Eurostat. [11]

Once all data are collected by region-year we formulate them into a panel. The panel is at the region-class-year and its dimensions are 218x45x17. Table A3 of the Web Appendix displays summary statistics for the variables of interest while Table A4 their correlation coefficients. The correlation between trademark applications at the region-class-year level is 0.43 with patent stock at the region-year level. Further, we plot the frequency of trademark applications by NUTS-2 region filed during 2000-2016 in Figure 1 and compare with patent applications filed at the EPO during the same period in Figure 2. One knowledgeable to European geography can swiftly correlate high patenting activity with Western German and Northern Italian regions. While trademark activity overlaps significantly, we also observe certain regions in Spain and Eastern Europe that engage more in trademarks than patents. At this aggregate level of analysis, the correlation is 0.74 while when we exclude regions in the top quartile of patenting activity the correlation decreases but remains high at 0.55.

[10] EPO does not yet grant patents with EU-wide coverage but a grant from this office allows applicants to register patents in all EU countries in addition to many non-EU countries, members of the EPO (Harhoff *et al.* 2009).
[11] https://ec.europa.eu/eurostat/web/regions/data/database

3.2. Data Configuration for Testing Hypothesis 2

We bundle years in three time periods: 2000-2006, 2007-2011 and 2012-2016. This is a standard practice in the regional diversification literature that ensures any new specialization in a region is not just an artifact of short-term fluctuations (Neffke et al., 2011).

For this part of the analysis, the size of the panel is 218x45x3 (i.e. number of regions times number of Nice classes times number of periods). To construct the trademark relatedness measure we adapt the metrics by Klinger and Hausman (2007) and Hidalgo *et al.*, (2007) to the trademark data at hand. We should note that are other similarity measures that employ cooccurrence data (Eck and Waltman, 2009). However, to be consistent with the baseline methodology of regional diversification studies including Balland *et al.*, (2019) we opt for the relatedness measure.

Note that for the baseline panel, if a trademark application claims more than one Nice class, then we count it in all the claimed classes. First, denote each NUTS-2 as a region *r* and consider each time period as a period *t*. For region *r,* there is a certain number of trademark applications that claim Nice class *i* and have been filed at period *t*. To compute for a region *r*, at period *t*, if it has a Revealed Comparative Advantage (RCA) in a Nice class *i,* we adopt the definition by Balassa (1965):

$$RCA_{r,i,t} = \frac{trademarks_{r,i,t} / \sum_i trademarks_{r,i,t}}{\sum_r trademarks_{r,i,t} / \sum_r \sum_i trademarks_{r,i,t}}$$

where $trademarks_{r,i,t}$ is the number of trademark applications filed by entities located in region *r* and have claimed Nice class *i* at period *t*. The $RCA_{r,i,t}$ is able to show that if region *r* has a disproportionately higher share of trademarks in Nice class *i* compared to the whole population's share, then we can infer that the region exhibits specialization in this class. In other words, it possesses an *RCA* in this class. Further, note the measure of diversification if $RCA_{r,i,t} > 1$:

$$x_{r,i,t} = \begin{cases} 1 \; if \; RCA_{r,i,t} > 1 \\ 0 \quad otherwise \end{cases}$$

where $x_{r,i,t}$ is employed to construct the dependent variable of the paper.

To measure the relatedness density for each region *r* for each Nice class *i* we first need to calculate the relatedness between classes *i* and *j* where *i≠j* for all the regions cumulatively. For the 218 regions we count the instances that class *i* has RCA>1 given that class *j* has RCA>1. This way, we obtain the probability $P(x_{i,t}|x_{j,t})$. Further, for the 218 regions we count the instances that class *j* has RCA>1 given that class *i* has RCA>1 obtaining the probability $P(x_{j,t}|x_{i,t})$. One example is Classes 6 and 16 which relate to metal and paper products respectively. For the period 2000-2006, $P(x_{6i,t}|x_{16,t}) = 0.19$ while $P(x_{16i,t}|x_{6,t}) = 0.39$. This implies that the probability of a region having an RCA in class 16 (paper) given that it has in class 6 (metal) is higher than the probability of having an RCA in class 16 (metal) given that it has in class 6 (paper).

To reconcile this asymmetric distance between trademark classes, Hausman and Klinger (2007) take the minimum of each conditional probability:

$$\varphi_{i,j} = \min\{P(x_{i,t}|x_{j,t}), P(x_{j,t}|x_{i,t})\}$$

For this project $\varphi_{i,j}$ can now populate a symmetric matrix 45x45 which shows the trademark space, in the same spirit that Hidalgo *et al.*, (2007) mapped the product space. We visualize this space for the period 2012-2016 in Figure 3A in a network while in Figure 3B in a matrix format.[12] To keep only significant connections, we show edges (connections) where $\varphi_{i,j}$>0.4. The size of each node shows the frequency of each Nice class while the shape/color shows whether the class refers to products or services.

First, we observe a partial fragmentation between the service- and product-related classes. Interestingly, two service classes (37 and 40) [13] are related strongly with multiple product classes. Second, there are many product classes that appear to be clustered together indicating that they are very likely to display RCA simultaneously within a region. For instance, the food-related product classes (29-33) display strong connectivity indicating that there is a high probability that a region will simultaneously have an RCA in all these products. Another example is classes 6-8 and 19-22; these include materials, machines and light tools and potential constructions employing such tools (e.g. furniture, kitchen utensils). To examine whether these connections are overall stable, we

[12] All the visualizations of connectivity have been made with the help of Grund's code (2015).
[13] Class 37: Building construction; repair; installation services. Class 40: Treatment of materials.

display the connectivity matrices for 2000-2006 and 2007-2011 periods in Figures A2 and A3 of the Web Appendix. As can be seen, the matrices are by and large similar.

The next step is to construct the main independent variable of interest; that of relatedness. This measure is calculated at the region *r*, Nice class *i*, period *t* level. We suppress the period notation and calculate it as:

$$RELATEDNESS\_DENSITY_{i,r} = \frac{\sum_{j \in r, j \neq i} \varphi_{ij}}{\sum_{j \neq i} \varphi_{ij}}$$

The above variable is the region's relatedness for class *i*; it is calculated as the sum of relatedness between class *i* and all other classes *j*, given that region *r* has an RCA>1 for class *j*, divided by the total sum of relatedness between class *i* and all other classes *j*. This measure essentially captures how embedded class *i* is in region *r* to its rest of the classes.

Figure 4 shows the average relatedness over all classes over the entire time period for each region. A comparison with Figure 2, the total number of trademark applications, shows no systematic correlation between the trademark activity and relatedness. A correlation at the regional level verifies this observation (ρ=-0.0587). This indicates that high trademark activity is not associated with high trademark relatedness; the latter is achieved by targeted trademark activity in classes that are closely related.

Finally, the dependent variable of diversification is formulated as $Entry_{r,i,t}$. It takes the value of 1 if region *r* has an RCA>1 in Nice Class *i* at period *t* given that it did not have in period *t-1* and 0 otherwise; in other words:

$$Entry_{r,i,t} = \begin{cases} 1 \; if \; x_{r,i,t} = 1 \;\&\; x_{r,i,t-1} = 0 \\ 0 \quad otherwise \end{cases}$$

This dependent variable shows whether a region exhibits a new specialization in class *i* at period *t*. Finally note that for the econometric analysis we also construct $TotalMarks_{i,r,t-1}$ which is the number of trademark applications claiming class *i* that region *r* has accumulated by period *t-1*. We measured it in thousands of trademark applications.

Naturally, the choice of double counting Nice classes may bias the results. Therefore, as robustness to the results, we re-visit the treatment of multiple Nice classes per trademark application. Instead of double counting trademark applications, we consider each trademark application as one count. In case the trademark application claims more than one Nice class, it is weighted based on the total classes it has claimed. Then, we re-compute all the key variables that we will employ in the econometric analysis. We denote them as $W\_Entry_{r,i,t}$, $W\_x_{r,i,t}$, $W\_RELATEDNESS\_DENSITY_{r,i,,t}$ and $W\_TotalMarks_{r,i,t-1}$.

Tables A5 and A6 of the Web Appendix provide summary statistics and correlations for all the variables employed in the analysis and the intermediate variables. Interestingly the correlations between the measures where we double count or weigh trademark classes are quite high indicating that this choice is not likely to alter the results. We re-visit this issue in sub-Section 5.2.

At this point, we should highlight a metric-related drawback of the trademark data. Industry- and technology-related studies of regional diversification are able to consider finer levels of sector disaggregation. For trademarks this is not possible as the Nice classification system does not have finer levels of disaggregation. Recently however, studies have exploited a key dimension of trademarks to infer more details over their characteristics. All trademarks disclose a Goods and Services Description (GSD). In there, the applicants describe the goods and services they wish to sell disclosing a wide array of products or services. Scholars are employing this information to measure business activity. For instance, Graham et al., (2019) identified words in the GSD that previously were not disclosed in any of the trademarks in the Nice class. They posited that such new words can be an indicator of product or service innovation.

Employing however keywords to reconfigure the population of trademarks to new, more disaggregated classes, is a daunting task that requires multiple steps and assumptions. Nonetheless, it is worth employing the words in the GSD to provide a crude reclassification of Nice classes. In particular, based on GSD words we double the number of classes a trademark application can be classified into. We proceed as follows. For each trademark in each Nice class *i*, we count all the words that are disclosed in GSD after we have excluded generic words such as “the”, “and” , “is” etc. For each Nice class we identify the ten most popular words. For instance, Nice class 10’s most popular words include “Dental”, “Medical”, “Apparatus”. Then we classify a trademark in Nice class *i_a* if the trademark discloses at least five of the ten most popular words; alternatively, we classify it in class *i_b*.

Via this process, we construct the aforementioned metrics based on these ninety pseudo-Nice classes. The premise is that if the results are driven exclusively by the small number of classes, then this analysis would provide substantially different results. Note these new measures as $N\_Entry_{r,i,t}$, $N\_x_{r,i,t}$, $N\_RELATEDNESS\_DENSITY_{r,i,,t}$ and $N\_StockMarks_{r,i,t-1}$. We should note that correlation between $N\_Entry_{r,i,t}$ and $N\_x_{r,i,t}$ is 0.53 while the correlation between $N\_Entry_{r,i,t}$ and $N\_RELATEDNESS\_DENSITY_{r,i,,t}$ is -0.01. Both of these correlations are similar to the correlations to the baseline analysis. Note that the panel for this analysis is 218x90x3.

4. Econometric Estimation

4.1. Testing Hypothesis 1

To test Hypothesis 1, the following formulation takes place:

$$Marks_{r,i,y} = \alpha_0 + \alpha_1 PatentStock_{r,y} + Region_r + Year_y + Class_i + \varepsilon_{r,i,y} \qquad (1)$$

where $Marks_{r,i,y}$ is the number of trademark applications filed at year y, claiming Nice class *i*, by entities located in region *r*. $PatentStock_{r,y}$ is the patent stock accumulated by entities located in region *r* by year y. To take into account heterogeneity we include $Region_r$, $Year_y$ and $Class_i$ which are region, year and Nice Class fixed effects respectively.

If α_1 is positive and statistically significant, then we find substantial evidence to support Hypothesis 1; that is, regions with increased technological capabilities will also develop an increase in trademark applications.

Since trademark applications by region are counts, we estimate the above equation via Poisson and Negative Binomial. Further, since for many region-class-year observations, trademark applications will be zero, we also estimate the equation via a zero-inflated Negative Binomial (Greene, 1994). The latter procedure estimates two regressions; a logistic regression which functions as a generation mechanism for the observations with zero trademark applications and a negative binomial regression that models the focal variable. For the logistic regression, the regressors should relate to the likelihood that an observation may have zero trademark applications. For this reason, we employ region-level variables that indicate size; these are region's area, GDP per capita and population. In all of these estimations standard errors are clustered at the region-class level to avoid serial correlation (Bertrand *et al.*, 2004).

We should note that for these baseline regressions we double count trademark applications that claim more than one Nice class. However, for robustness we also consider trademark applications weighted by Nice classes they claim.

4.2. Testing Hypothesis 2

To test Hypothesis 2, the following formulation takes place:

$$Entry_{r,i,t} = \beta_0 + \beta_1 RELATEDNESS\_DENSITY_{r,i,t-1} + \beta_2 TotalMarks_{r,i,t-1} + RegionPeriod_{r,t} + Class_i + \varepsilon_{r,i,t} \quad (2)$$

To take into account regional heterogeneity we include region-period dummies: $RegionPeriod_{r,t}$. We also include Nice class dummies; i.e. $Class_i$.

The coefficient of interest is β_1. If $\beta_1 > 0$, then there is substantial evidence to support Hypothesis 2; i.e. relatedness plays a positive role in new specializations in trademark activity. Note that $RELATEDNESS\_DENSITY$ is standardized for all the regressions (Xiao *et al.*, 2018).

Two points merit attention. First, as it is common in this literature, we only include region-class-period observations where they display no RCA>1 in period *t-1* (i.e. $x_{r,i,t-1} = 0$). In other words, we only include observations that can potentially change into an RCA>1. Had they already displayed an RCA>1 in *t-1*, then they could not add any information in the relationship between $RELATEDNESS\_DENSITY$ and *Entry*. Second, given the large amount of fixed effects, we estimate equation 2 and all the subsequent regressions via Ordinary Least Squares (OLS). While the dependent variable is a dummy, estimators such as probit or logit can lead to biased estimates due to the large number of dummies (Greene 2012; Boschma *et al.* 2013). Finally, as in sub-Section 4.1. the standard errors are clustered at the region-class level.

5. Results

5.1. Results of Testing Hypothesis 1

Table 1 displays estimations of equation 1. Column 1 is estimated via Poisson. The coefficient of $PatentStock$ can be interpreted as follows: a region's increase in the patent stock by 1000 patent applications, will also be accompanied by an increase in trademark applications in a particular class by exp(0.0280)-1=2.8%. In Column 2, the same model is estimated via Negative Binomial while in Column 3, via zero-inflated Negative Binomial. The coefficient in both cases is higher than Poisson and in all cases is significant at the 1% level. Since results between the three estimators are qualitatively similar, the estimator hereafter is the zero-inflated Negative Binomial. In Column 4, instead of $PatentStock_{r,y}$ we include $PatentStock_{r,y-1}$. The coefficient is again qualitatively similar. In Columns 5 and 6, instead of $Marks$ we consider $MarksW$ which is trademark applications weighted by the number of Nice classes. In both columns, patent stock is strongly and positively associated with trademark applications. Overall, the results provide strong evidence in support of Hypothesis 1.

It is also interesting to examine whether this strong relationship is different for product and service trademark applications. Table A7 of the Web Appendix separates the panel to observations pertaining to product and service observations and performs the zero-inflated Binomial regressions. While both types of trademark applications are strongly related with technological capabilities, service applications exhibit a larger coefficient. This finding echoes studies that have shown that the growth in service sector is positively influenced by inter-sectoral spillovers pointing to the benefits of an advanced manufacturing sector (Van Stel and Nieuwenhuijsen 2004; Mameli et al., 2012). In a recent study, Horváth and Rabetino (2019) also point to the importance of an advanced manufacturing sector in the growth of the service sector. A strong indicator of such a manufacturing sector is its advanced technological capabilities as we measure in this analysis. The intuition behind this literature is that the service sector is more likely to be developed to support and promote the manufacturing sector. An alternative explanation could be that of an evolution; i.e. a region's economy can evolve from a strong manufacturing sector to include an advanced service sector.

5.2. Results of Testing Hypothesis 2

Table 2 tests Hypothesis 2 by estimating equation 2. Column 1 includes all observations. The coefficient of *RELATEDNESS_DENSITY* is positive and significant at the 1% level providing support for Hypothesis 2. Since the variable *RELATEDNESS_DENSITY* is standardized, the magnitude of the coefficient can be interpreted as follows: a one standard deviation increase of $RELATEDNESS\_DENSITY_{r,i,,t-1}$ from its mean will increase the likelihood that region *r* will exhibit new specialization in class *i* at period *t* by 20.2 percentage units. When we separate the new specializations in product and service classes, we observe that the coefficient of $RELATEDNESS\_DENSITY$ is marginally higher for the product classes (Columns 2 and 3). To investigate on this difference further, we consider a *Service* dummy which takes the value of 1 for observations relating to service classes and 0 otherwise. Then in Column 4 we consider all classes and include the interaction $RELATEDNESS\_DENSITY\_x\_Service$. Note that the *Service* dummy cannot be included as we already include Nice class dummies. The coefficient is quite small and insignificant. Therefore, there does is no heterogeneous role of *RELATEDNESS_DENSITY* in these two types of new specializations.

To check for the sensitivity of our results, we consider each period (2007-2011 and 2012-2016) separately and perform the same regressions. Results for each period are displayed in Tables A8 and A9 of the Web Appendix. As can be seen the coefficient of *RELATEDNESS_DENSITY* is positive and significant in both periods indicating that the result is consistent throughout the entire time period studied.

As an additional robustness to our results, we re-visit the treatment of multiple Nice classes per trademark application. Instead of double counting trademark applications, we now consider each trademark application as one count and employ the measures $W\_Entry_{r,i,t}$, $W\_RELATEDNESS\_DENSITY_{r,i,,t-1}$ and $W\_StockMarks_{r,i,t-1}$ when estimating equation 2. Results are displayed in Table 3 and are qualitatively similar to the baseline results. Finally, to provide further robustness on the small number of Nice classes, we employ the measure we constructed in sub-Section 4.2. and re-estimate equation 2. Results are displayed in Table 4 and are quite similar to the baseline results. Overall, the empirical findings provide strong support in favor of Hypothesis 2.

6. Policy Implications and Discussion

New regional specializations have been receiving increased policy interest over the past decades in Europe. In this paper, we have shown that trademark applications are closely linked to the technological capabilities of a region. The intuition is that trademark applications are approximating value-added marketing and commercialization activities which are essential for exploiting technological advancements.

Having empirically established this relationship we examined new trademark specializations within regions. In this section, we provide an additional crude piece of evidence supporting the generation of new trademark specializations at the regional level.

With the data we collected on the GDP by NUTS-2 region we compute the average GDP growth for time periods 2006-2011 and 2012-2016. First note that the correlation between the number of new trademark specializations per region-period and its GDP growth is 0.1517. While it is positive and statistically different from zero, its small size warrants additional investigation. To this end we run a simple regression and the estimates are the following:

$$GDPGrowth_{r,t} = 0.28^{a} + 0.006^{b} New\ Specializations_{r,t} - 0.001^{b} GDPBilEur_{r,t-1} + 0.036^{a} PopMillions_{r,t-1} - 0.109^{a} Trend_{t} \quad R^2=0.1827$$

Where a and b stand for 1% and 5% significance respectively; standard errors are clustered at the region level. Overall, this simple regression shows that new trademark specializations are associated positively with GDP growth. While by no means conclusive, this simple association, coupled with the paper's findings, informs policies aiming at new trademark specializations associated with marketing and innovative activities. Such activities should pay special focus on the region's existing related capabilities and advantages. [14]

7. Conclusion

Scholars have pointed to the importance of trademarks for firm strategy, innovation and value. However, regional-level analyses of trademarks are rarer. Our testbed is the 218 NUTS-2 regions of 16 EU countries over 2000-2016.

[14] Embarking from the latter statement it is useful to note the recent study by Farinha *et al.*, (2019) that dissects the potential different mechanisms of relatedness in new job specializations. According to their study, these mechanisms are i) complementarity, in the sense that jobs that complement each other are more likely to be related, ii) similarity, signifying that types of jobs may require overlapping skill sets in the spirit of Neffke and Henning (2013) and iii) local synergies. Decomposing trademark relatedness in these three mechanisms is neither straightforward nor within the scope of this study. To what extent each mechanism promotes new trademark specializations can be a timely topic of regional policy; especially when considering that trademark classes may be associated with different technology/information intensity (Mendonça and Fontana 2011) and in view of our findings that they are strongly linked to the region's technological capabilities.

Following the first objective, we showed that there is strong link between a region's patenting and trademark activity. This evidence supports firm-level studies that have shown that technological capabilities will require marketing activities to be commercialized. Following the second objective we examine how new trademark specializations are generated. We show that the region's existing related trademark activities can promote new trademark specializations.

This study contributes to the regional diversification literature which has received increased scientific interest over the last decade. Further, within the EU, the concept of Smart Specialization has become an integral part of regional policy. Until now however, trademark activity had not been considered primarily due to the unavailability of the population of data.

The findings of this paper inform regional policy, especially through the lens of Smart Specialization. Innovation appears to be closely related to marketing and commercialization activities in a region. Further, regions can branch out more easily to new activities that are related to their existing comparative advantages.

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Table 1. Role of patent stock in trademark activity.

VARIABLES	(1) $Marks$	(2) $Marks$	(3) $Marks$	(4) $Marks$	(5) $MarksW$	(6) $MarksW$
$PatentStock_{r,y}$	0.028***	0.077***	0.066***		0.049***	
	(0.010)	(0.008)	(0.006)		(0.007)	
$PatentStock_{r,y-1}$				0.048***		0.034***
				(0.006)		(0.008)
Observations	166,770	166,770	166,770	155,835	166,770	155,835

Notes: Column 1 is estimated via Poisson. Column 2 via Negative Binomial. Columns 3-6 are estimated via zero-inflated Negative Binomial; the logistic regression in every case includes the region's area, GDP per capita and population. All columns include region, Nice class and year dummies. Standard errors are clustered at the region-class level and displayed in the parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2. Role of relatedness on new trademark specializations.

VARIABLES	(1) All Classes	(2) Product Classes	(3) Service Classes	(4) All Classes
$RELATEDNESS\_DENSITY$	0.202***	0.246***	0.192***	0.201***
	(0.012)	(0.017)	(0.021)	(0.0117)
$RELATEDNESS\_DENSITY\_x\_Service$				0.00334
				(0.0104)
$TotalMarks$	0.096***	0.070*	0.166***	0.0955***
	(0.033)	(0.041)	(0.046)	(0.0334)
Constant	0.231***	0.258***	0.193***	0.232***
	(0.022)	(0.022)	(0.020)	(0.0221)
Observations	11,831	8,716	3,115	11,831
R-squared	0.125	0.138	0.286	0.125

Notes: The dependent variable in all regressions is *Entry*. All regressions are estimated via OLS. All columns include region-period dummies and Nice class dummies. Columns 1 and 4 consider all Nice classes. Column 2 considers only the observations relating to product classes while Column 3 service classes. Standard errors are clustered at the region-class level and displayed in the parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3. Robustness to Table 2. Consider weighing of trademarks.

VARIABLES	(1) All Classes	(2) Product Classes	(3) Service Classes	(4) All Classes
$W\_RELATEDNESS\_DENSITY$	0.258***	0.284***	0.231***	0.258***
	(0.014)	(0.020)	(0.026)	(0.014)
$W\_RELATEDNESS\_DENSITY\_x\_Service$				-0.007
				(0.010)
$W\_TotalMarks$	0.242**	0.225*	0.278	0.241**
	(0.102)	(0.127)	(0.191)	(0.102)
Constant	0.276***	0.195***	0.222***	0.274***
	(0.023)	(0.018)	(0.022)	(0.023)
Observations	12,172	9,060	3,112	12,172
R-squared	0.121	0.133	0.285	0.121

Notes: The dependent variable in all regressions is W_Entry. All regressions are estimated via OLS. All columns include region-period dummies and Nice class dummies. Columns 1 and 4 consider all Nice classes. Column 2 considers only the observations relating to product classes while Column 3 service classes. Standard errors are clustered at the region-class level and displayed in the parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4. Robustness to Table 2. Consider finer levels of Nice class disaggregation.

VARIABLES	(1)
$N\_RELATEDNESS\_DENSITY$	0.242***
	(0.008)
$N\_StockMarks$	0.054
	(0.037)
Constant	0.243***
	(0.021)
Observations	25,063
R-squared	0.094

Notes: The dependent variable is N_Entry. The regression is estimated via OLS. It includes region-period and the pseudo-Nice class dummies. Standard errors are clustered at the region-class level and displayed in the parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Figure 1. Frequency of trademark applications by NUTS-2 region (2000-2016).

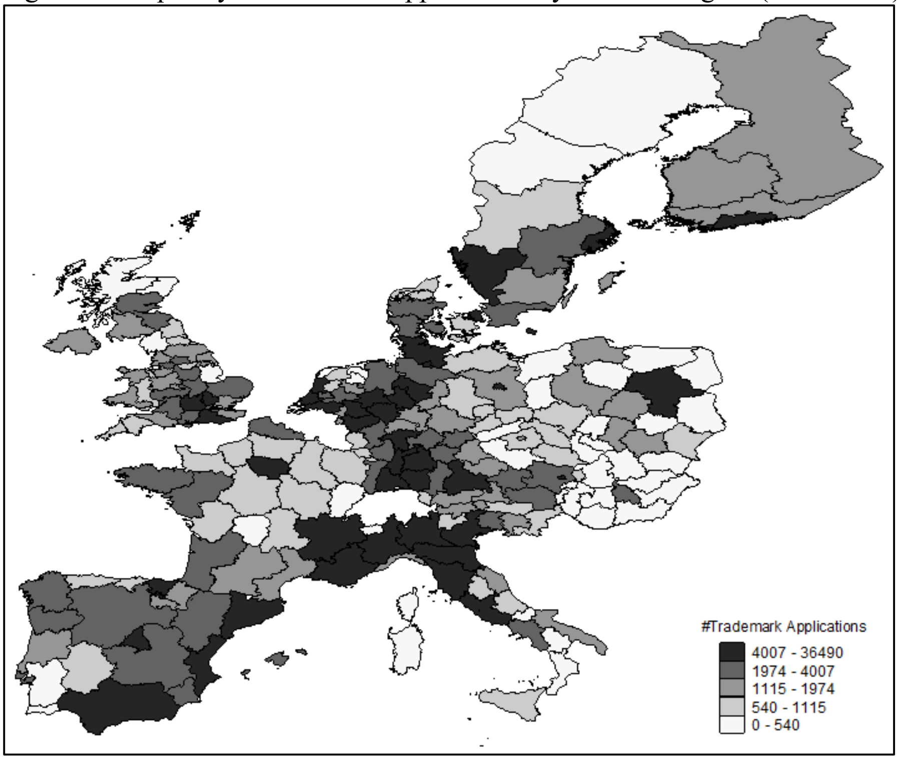


Figure 2. Frequency of patent applications by NUTS-2 region (2000-2016).

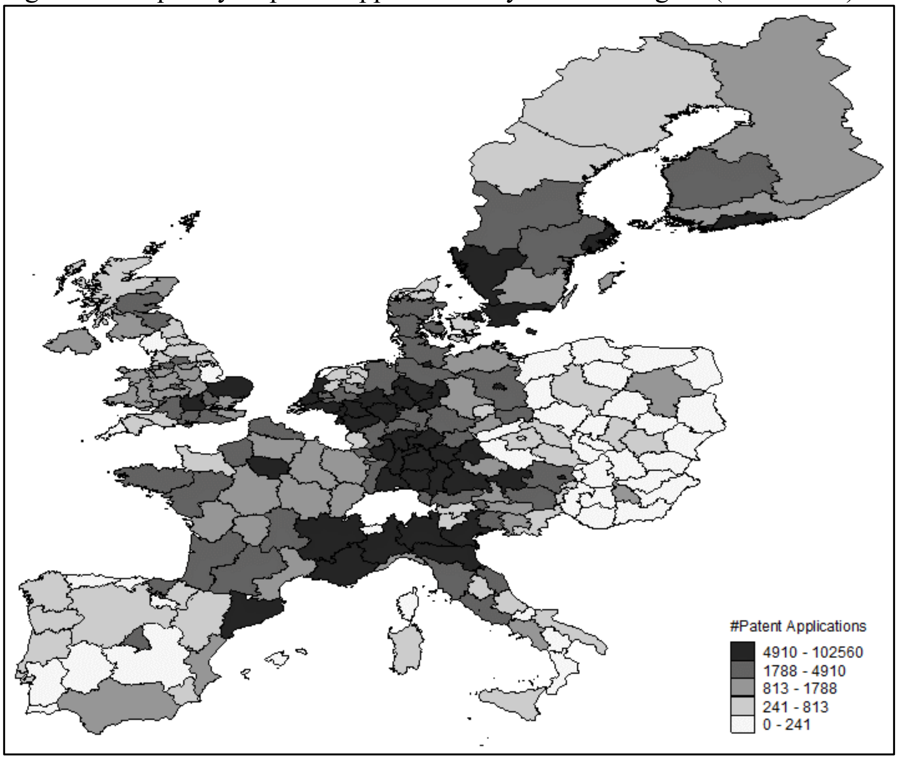
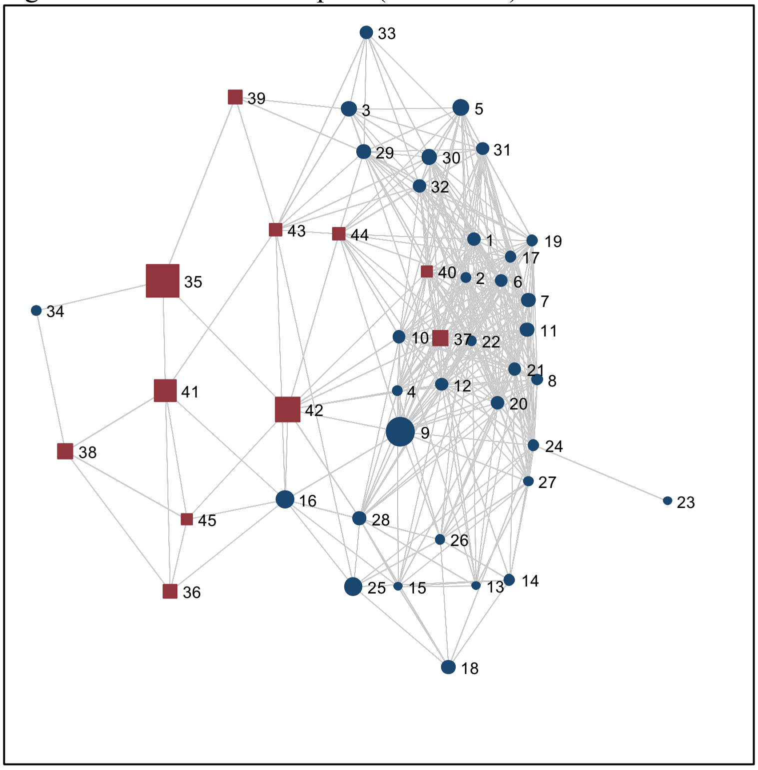


Figure 3A. The trademark space (2012-2016). Network format.



Notes: the shape and color of each node signifies the type of Nice class (square and red denote service classes while circle and blue denote product classes). The size of each node shows the frequency of each class in the data.

Figure 3B. The trademark space (2012-2016). Matrix format.

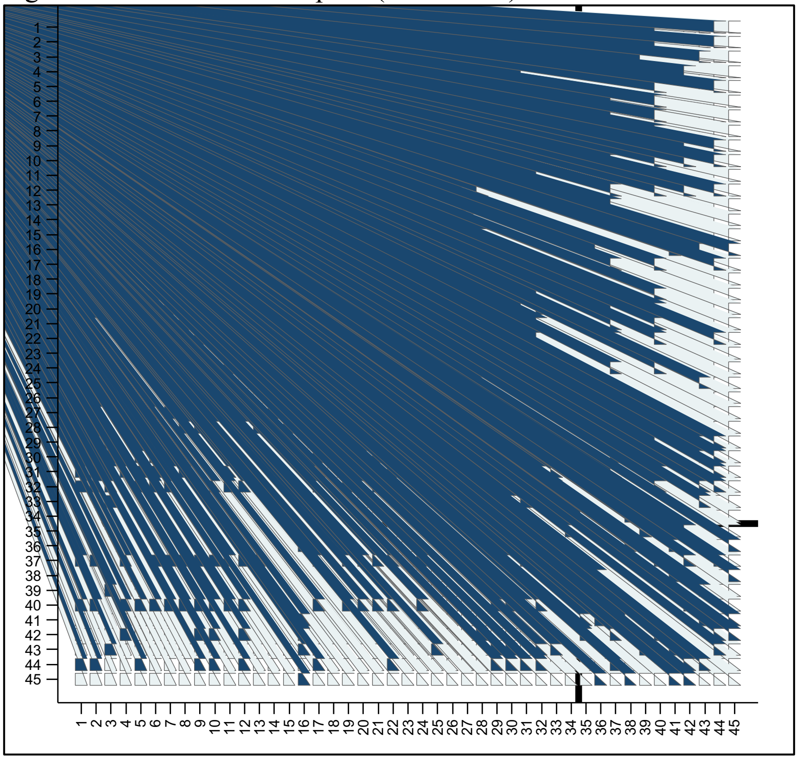
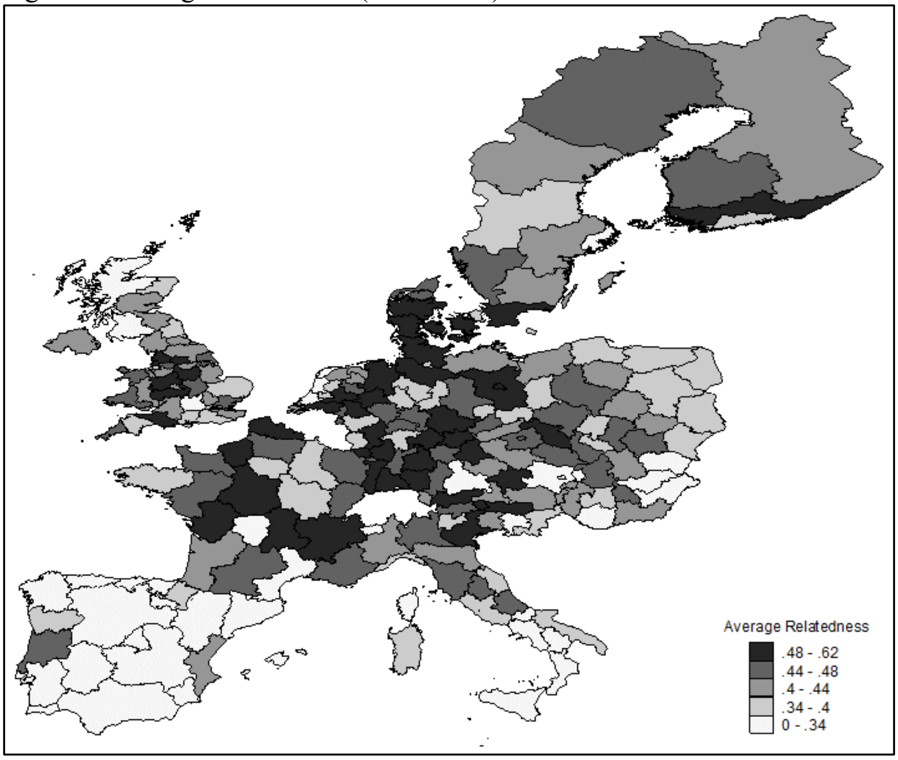


Figure 4. Average Relatedness (2000-2016).



Web Appendix

Table A1. Nice classes with their headings.

Class No.	Nice Class Heading
1	Chemicals used in industry, science and photography, as well as in agriculture, horticulture and forestry; unprocessed artificial resins, unprocessed plastics; manures; fire extinguishing compositions; tempering and soldering preparations; chemical substances for preserving foodstuffs; tanning substances; adhesives used in industry
2	Paints, varnishes, lacquers; preservatives against rust and against deterioration of wood; colorants; mordants; raw natural resins; metals in foil and powder form for use in painting, decorating, printing and art
3	Bleaching preparations and other substances for laundry use; cleaning, polishing, scouring and abrasive preparations; soaps; perfumery, essential oils, cosmetics, hair lotions; dentifrices
4	Industrial oils and greases; lubricants; dust absorbing, wetting and binding compositions; fuels (including motor spirit) and illuminants; candles and wicks for lighting
5	Pharmaceuticals, medical and veterinary preparations; sanitary preparations for medical purposes; dietetic food and substances adapted for medical or veterinary use, food for babies; dietary supplements for humans and animals; plasters, materials for dressings; material for stopping teeth, dental wax; disinfectants; preparations for destroying vermin; fungicides, herbicides
6	Common metals and their alloys; metal building materials; transportable buildings of metal; materials of metal for railway tracks; non-electric cables and wires of common metal; ironmongery, small items of metal hardware; pipes and tubes of metal; safes; ores
7	Machines and machine tools; motors and engines (except for land vehicles); machine coupling and transmission components (except for land vehicles); agricultural implements other than hand-operated; incubators for eggs; automatic vending machines
8	Hand tools and implements (hand-operated); cutlery; side arms; razors
9	Scientific, nautical, surveying, photographic, cinematographic, optical, weighing, measuring, signalling, checking (supervision), life-saving and teaching apparatus and instruments; apparatus and instruments for conducting, switching, transforming, accumulating, regulating or controlling electricity; apparatus for recording, transmission or reproduction of sound or images; magnetic data carriers, recording discs; compact discs, DVDs and other digital recording media; mechanisms for coin-operated apparatus; cash registers, calculating machines, data processing equipment, computers; computer software; fire-extinguishing apparatus
10	Surgical, medical, dental and veterinary apparatus and instruments; artificial limbs, eyes and teeth; orthopedic articles; suture materials
11	Apparatus for lighting, heating, steam generating, cooking, refrigerating, drying, ventilating, water supply and sanitary purposes
12	Vehicles; apparatus for locomotion by land, air or water
13	Firearms; ammunition and projectiles; explosives; fireworks
14	Precious metals and their alloys; jewellery, precious stones; horological and chronometric instruments
15	Musical instruments
16	Paper and cardboard; printed matter; bookbinding material; photographs; stationery; adhesives for stationery or household purposes; artists' materials; paintbrushes; typewriters and office requisites (except furniture); instructional and teaching material (except apparatus); plastic materials for packaging; printers' type; printing blocks
17	Unprocessed and semi-processed rubber, gutta-percha, gum, asbestos, mica and substitutes for all these materials; plastics in extruded form for use in manufacture; packing, stopping and insulating materials; flexible pipes, not of metal
18	Leather and imitations of leather; animal skins, hides; trunks and travelling bags; umbrellas and parasols; walking sticks; whips, harness and saddlery
19	Building materials (non-metallic); non-metallic rigid pipes for building; asphalt, pitch and bitumen; non-metallic transportable buildings; monuments, not of metal

20	Furniture, mirrors, picture frames; unworked or semi-worked bone, horn, ivory, whalebone or mother-of-pearl; shells; meerschaum; yellow amber
21	Household or kitchen utensils and containers; combs and sponges; brushes (except paintbrushes); brush-making materials; articles for cleaning purposes; steelwool; unworked or semi-worked glass (except glass used in building); glassware, porcelain and earthenware
22	Ropes and string; nets; tents, awnings and tarpaulins; sails; sacks; padding and stuffing materials (except of paper, cardboard, rubber or plastics); raw fibrous textile materials
23	Yarns and threads, for textile use
24	Textiles and substitutes for textiles; bed covers; table covers
25	Clothing, footwear, headgear
26	Lace and embroidery, ribbons and braid; buttons, hooks and eyes, pins and needles; artificial flowers
27	Carpets, rugs, mats and matting, linoleum and other materials for covering existing floors; wall hangings (non-textile)
28	Games and playthings; gymnastic and sporting articles; decorations for Christmas trees
29	Meat, fish, poultry and game; meat extracts; preserved, frozen, dried and cooked fruits and vegetables; jellies, jams, compotes; eggs; milk and milk products; edible oils and fats
30	Coffee, tea, cocoa and artificial coffee; rice; tapioca and sago; flour and preparations made from cereals; bread, pastries and confectionery; edible ices; sugar, honey, treacle; yeast, baking-powder; salt; mustard; vinegar, sauces (condiments); spices; ice
31	Agricultural, horticultural and forestry products; raw and unprocessed grains and seeds; fresh fruits and vegetables; natural plants and flowers; live animals; foodstuffs for animals; malt
32	Beers; mineral and aerated waters and other non-alcoholic beverages; fruit beverages and fruit juices; syrups and other preparations for making beverages
33	Alcoholic beverages (except beers)
34	Tobacco; smokers' articles; matches
35	Advertising; business management; business administration; office functions
36	Insurance; financial affairs; monetary affairs; real estate affairs
37	Building construction; repair; installation services
38	Telecommunications
39	Transport; packaging and storage of goods; travel arrangement
40	Treatment of materials
41	Education; providing of training; entertainment; sporting and cultural activities
42	Scientific and technological services and research and design relating thereto; industrial analysis and research services; design and development of computer hardware and software
43	Services for providing food and drink; temporary accommodation
44	Medical services; veterinary services; hygienic and beauty care for human beings or animals; agriculture, horticulture and forestry services
45	Legal services; security services for the protection of property and individuals; personal and social services rendered by others to meet the needs of individuals

Notes: The headings of Nice classes are based on the 2016 edition:
https://www.wipo.int/classifications/nice/en/ITsupport/Version20160101/index.html

Table A2. Distribution of trademark applications by country of applicant.

Country	Number	Country	Number	Country	Number
AD	237	FR	71,403	MX	2,650
AE	1,893	GB	118,863	MY	797
AG	100	GG	540	NL	38,753
AR	1,385	GI	668	NO	2,138
AT	21,399	GR	4,557	NZ	2,081
AU	5,136	HK	9,178	PA	836
BB	674	HR	342	PE	169
BE	17,383	HU	2,897	PH	138
BG	2,865	ID	291	PK	142
BM	1,091	IE	10,921	PL	17,560
BR	3,770	IL	3,591	PT	10,626
BS	815	IM	860	QA	220
BZ	227	IN	2,388	RO	3,271
CA	13,382	IS	342	RU	648
CH	25,799	IT	89,688	SA	663
CL	1,589	JE	715	SC	264
CN	16,117	JO	258	SE	26,924
CO	658	JP	23,324	SG	1,927
CR	106	KR	7,128	SI	1,789
CU	141	KW	174	SK	1,828
CW	367	KY	1,459	SM	455
CY	3,565	LB	441	TH	1,184
CZ	5,813	LI	1,175	TN	200
DE	175,892	LK	281	TR	2,828
DK	15,607	LT	1,331	TW	8,623
DO	199	LU	10,926	US	173,873
EC	168	LV	729	UY	267
EE	1,900	MA	128	VE	145
EG	195	MC	786	VG	3,594
ES	86,166	MT	2,488	ZA	2,580
FI	11,932	MU	491		

Note: Countries and dependent territories with fewer than 100 trademark application filed over 2000-2016 are not displayed for brevity.

Table A3. Summary statistics of annual observations for region-class observation units.

Variable	Obs	Mean	Std. Dev.
$Marks_{r,i,y}$	166,770	11.88	33.53
$MarksW_{r,i,y}$	166,770	4.12	11.25
$PatentStock_{r,y}$	166,770	1.31	3.25
$PatentStock_{r,y-1}$	155,835	1.33	3.29
$GDPperCapita_{r,y}$ (In Thousand Euros)	166,770	26.17	14.48
$Area_{r}$ (In Square Miles)	166,770	16252.6	23043.62
$Population_{r,y}$ (In Millions)	166,770	1.96	1.56

Table A4. Correlation matrix of annual observations for region-class observations units.

	$\boldsymbol{Marks_{r,i,y}}$	$\boldsymbol{MarksW_{r,i,y}}$	$\boldsymbol{PatentStock_{r,y}}$	$\boldsymbol{PatentStock_{r,y-1}}$	$\boldsymbol{PatentStock_{r,y-1}}$	$\boldsymbol{Area_{r}}$	$\boldsymbol{Population_{r,y}}$
$Marks_{r,i,y}$	1						
$MarksW_{r,i,y}$	0.95	1					
$PatentStock_{r,y}$	0.43	0.40	1				
$PatentStock_{r,y-1}$	0.43	0.40	1.00	1			
$GDPperCapita_{r,y}$	0.34	0.31	0.33	0.33	1		
$Area_{r}$	-0.03	-0.02	-0.06	-0.07	-0.10	1	
$Population_{r,y}$	0.40	0.40	0.52	0.52	0.01	0.12	1

Table A5. Summary statistics for region-class-period observations testing Hypothesis 2.

Variable	Observations	Mean	Std. Dev.
$Entry_{r,i,t}$	19,620	0.13	0.33
$Entry_{r,i,t}$ given $Entry_{r,i,t-1}$=0	11,831	0.21	0.41
$x_{r,i,t}$	29,430	0.40	0.49
$RELATEDNESS\_DENSITY_{r,i,,t-1}$	19,620	0.41	0.11
$TotalMarks_{r,i,t-1}$	19,620	0.09	0.27
$W\_Entry_{r,i,t}$	19620	0.13	0.33
$W\_Entry_{r,i,t}$ given $W\_Entry_{r,i,t-1}$=0	12172	0.20	0.40
W_$x_{r,i,t}$	29430	0.38	0.49
$W\_RELATEDNESS\_DENSITY_{r,i,,t-1}$	19620	0.39	0.11
$W\_TotalMarks_{r,i,t-1}$	19,620	0.03	0.09
$Service_i$	29,430	0.24	0.43

Notes: *Service* is at the class level. The rest of variables are at the region-class-period level. $RELATEDNESS\_DENSITY_{r,i,,t-1}$ is not standardized in this Table and Table A6. In the estimations, $RELATEDNESS\_DENSITY_{r,i,,t-1}$ is standardized.

Table A6. Correlation matrix for region-class-period observations testing Hypothesis 2.

	$Entry_{r,i,t}$	$x_{r,i,t}$	$RDENS_{r,i,,t-1}$*	$TM_{r,i,t-1}$**	$W\_Entry_{r,i,t}$	$W\_x_{r,i,t}$	$W\_RDENS_{r,i,,t-1}$*	$W\_TM_{r,i,t-1}$**	$Service_i$
$Entry_{r,i,t}$	1								
$x_{r,i,t}$	0.4654	1							
$RDENS_{r,i,,t-1}$*	-0.0035	0.2295	1						
$TM_{r,i,t-1}$**	-0.0592	0.1248	0.0065	1					
$W\_Entry_{r,i,t}$	0.5739	0.3025	0.0201	-0.0502	1				
$W\_x_{r,i,t}$	0.2711	0.7643	0.2204	0.1128	0.4795	1			
$W\_RDENS_{r,i,,t-1}$*	0.0001	0.1746	0.7459	-0.0396	0.0077	0.2157	1		
$W\_TM_{r,i,t-1}$**	-0.0643	0.1392	0.0163	0.9579	-0.0568	0.1384	-0.0109		
$Service_i$	-0.0183	-0.0455	-0.0835	0.1031	0.0082	-0.0158	-0.0569	0.0591	1

Notes:
* $RDENS_{r,i,,t-1}$ and $W\_RDENS_{r,i,,t-1}$ stand for $RELATEDNESS\_DENSITY_{r,i,,t-1}$ and $W\_RELATEDNESS\_DENSITY_{r,i,,t-1}$ $r$espectively.
** $TM_{r,i,t-1}$ stand $W\_TM_{r,i,t-1}$ stand for $TotalMarks_{r,i,t-1}$ and W_$TotalMarks_{r,i,t-1}$ respectively.

Table A7. Role of patent stock in trademark activity. Separate by product and service Nice classes.

VARIABLES	(1) $Marks$	(3) $Marks$	(5) $Marks$
$PatentStock_{r,y}$	0.052***	0.096***	0.078***
	(0.007)	(0.010)	(0.008)
$Service$			0.493***
			(0.008)
$PatentStock_{r,y}\_x\_Service$			0.016***
			(0.002)
Observations	126,004	40,766	166,770

Notes: All Columns are estimated via zero-inflated Negative Binomial. All columns include region and year dummies. Columns 1 and 2 also include Nice class dummies. Column 1 includes only these region-class-year observations pertaining to product classes while Column 2 to service classes. Column 3 considers the entire panel. Standard errors are clustered at the region-class level and displayed in the parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A8. Estimate Table 1 only for the period 2007-2011.

VARIABLES	(1) All Classes	(2) Product Classes	(3) Service Classes	(4) All Classes
$RELATEDNESS\_DENSITY$	0.199***	0.234***	0.183***	0.199***
	(0.0164)	(0.0245)	(0.0305)	(0.0164)
$RELATEDNESS\_DENSITY\_x\_Service$				0.00679
				(0.0152)
$TotalMarks$	0.198**	0.161	0.228	0.197**
	(0.0805)	(0.0992)	(0.162)	(0.0805)
Observations	5,952	4,374	1,578	5,952
R-squared	0.124	0.146	0.271	0.124

Notes: The dependent variable in all regressions is *Entry*. All regressions are estimated via OLS. All columns include region dummies and Nice class dummies. Columns 1 and 4 consider all classes. Column 2 considers only the observations relating to product classes while Column 3 service classes. Standard errors are clustered at the region-class level and displayed in the parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A9. Estimate Table 1 only for the period 2012-2016.

VARIABLES	(1) All Classes	(2) Product Classes	(3) Service Classes	(4) All Classes
$RELATEDNESS\_DENSITY$	0.210***	0.269***	0.209***	0.210***
	(0.0162)	(0.0244)	(0.0297)	(0.0162)
$RELATEDNESS\_DENSITY\_x\_Service$				0.00268
				(0.0139)
$TotalMarks$	0.0747**	0.0383	0.167***	0.0747**
	(0.0354)	(0.0392)	(0.0446)	(0.0354)
Observations	5,879	4,342	1,537	5,879
R-squared	0.133	0.136	0.311	0.133

Notes: The dependent variable in all regressions is *Entry*. All regressions are estimated via OLS. All columns include region dummies and Nice class dummies. Columns 1 and 4 consider all classes. Column 2 considers only the observations relating to product classes while Column 3 service classes. Standard errors are clustered at the region-class level and displayed in the parentheses. *** p<0.01, ** p<0.05, * p<0.1

Figure A1. Frequency (in tens of thousands) of Nice classes in the population of trademark applications.

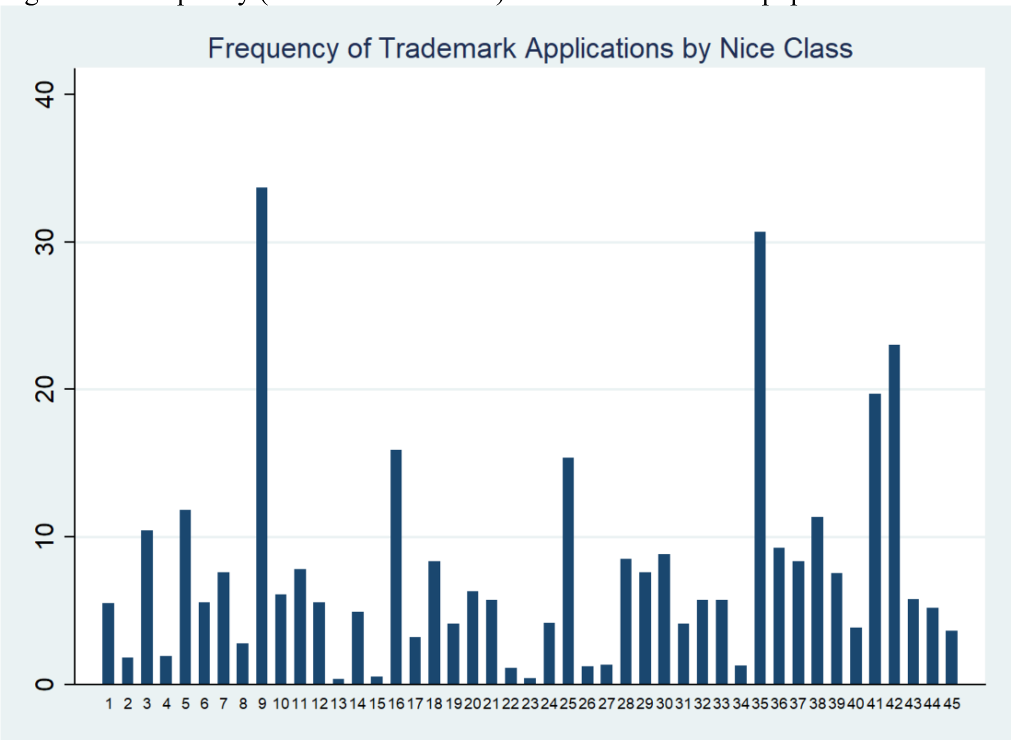


Figure A2. The trademark space (2000-2006). Matrix format.

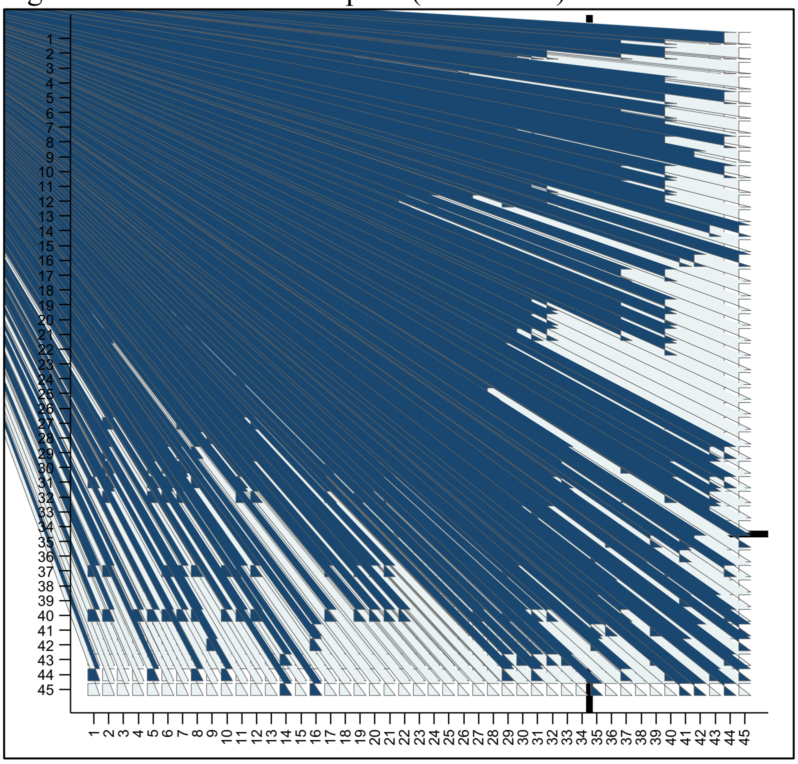


Figure A3. The trademark space (2007-2011). Matrix format.