IMMIGRATION AND INNOVATION IN EUROPEAN REGIONS*

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Abstract

The pooling of people with diverse backgrounds in particular areas may boost the creation of new ideas, knowledge spillovers, entrepreneurship and economic growth. In this paper we measure the impact of the size, skills and diversity of immigration on innovativeness of host regions. For this purpose we construct a panel of data on 170 regions in Europe (NUTS 2 level) for the period 1991-2001. Innovation outcomes are measured by means of the number and types of patent applications. Given the geographical concentration and subsequent diffusion of innovation activity, and the spatial selectivity of immigrant settlement patterns, we take account of spatial dependence and of endogeneity of immigrant settlement in the econometric modelling. We find that an increase in patent applications in a region is associated with (i) net immigration; (ii) the share of foreigners in the population of the region; (iii) the average skill level of the immigrants; and (iv) the cultural diversity of the immigrants. The magnitude of these effects varies between types of patents.

JEL classification: J61, O31, R23

Key words: immigration, cultural diversity, economic growth, innovation, spatial autocorrelation

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1. Introduction

The more than doubling of the number of foreign-born residents of developed countries since 1980 triggered a high level of research activity regarding the economic consequences of immigration. Yet many issues remain of concern to researchers, politicians and the general public. Much of the literature provides rather conclusive evidence that the *short-run* economic impact of an influx of foreigners on the host population is either positive (for example, an increase in demand; an increase in wages of those whose skills complement those of the arrivals; lower prices; a greater variety of goods and services) or only mildly negative (for example, a slight decrease of wages of those who are close substitutes for the new arrivals; an increase in the price of rental accommodation; a trade balance deterioration).[1] Far less is known about the *long-run* economic impact. Yet the preference of many host countries to recruit highly skilled workers (as revealed by their selection processes) is grounded in the belief that such workers will integrate more easily, lower the public funding that is required for education and training,[2] and boost long-run economic growth.

In this paper we focus on a specific driver of economic growth, namely innovation, and investigate empirically whether there is a positive impact of immigration on innovation. Migrants can contribute to innovation in various ways. They contribute to the population growth of cities, which reinforces agglomeration – with positive benefits for innovation and growth (e.g., Audretch, 1998; Gordon and McCann, 2005; Kerr, 2010). Moreover, their skills, their youthfulness and their self-selection in terms of ability, risk-taking and entrepreneurship may all have positive impacts on innovation (e.g., Poot, 2008). Furthermore, migrants increase the ethnic and cultural diversity of the cities they settle in and it is well known, particularly since the work of Jacobs (1961, 1969), that more diverse cities are more innovative and prosperous.

However, the empirical research on the links between immigration and innovation is still very recent and limited to about ten studies using predominantly North American data. Given that growth in the foreign-born population since 1980 has been faster in Europe than anywhere else in the world (e.g. Longhi et al. 2010b), research on the impact of this immigration on innovation activity in Europe is warranted and had not been conducted previously, except for a study of innovation in German regions (Niebuhr, 2010) and another in the city of London (Lee and Nathan, 2010). The present paper takes therefore a European

[1] Recent reviews include Hanson (2008), Pekkala Kerr and Kerr (2009) and Longhi et al. (2010a).

[2] However, Hunt (2009) finds with U.S. data that the graduate training in the US of foreign-born workers yields a greater net benefit than recruiting a worker with equivalent foreign training.

perspective and aims to identify the impact of immigration on patenting at a regional level across 12 European countries.

Essentially, there are five mechanisms through which immigration may boost innovation. These may be referred to as the *population scale* effect, the *population density* effect, the *migrant share* effect, the *skill composition* effect and the *migrant diversity* effect. The first two of these effects applies to the domestic population also and will be taken into account with other local determinants of immigration. The second, third and fourth effect are specific to immigration only and are the focus of the paper. Our empirical research considers these effects individually, but also jointly. Of course, to operationalise such effects, we must define these more precisely. For example, the host economy may benefit from an influx of highly skilled immigrants, but also from an influx of immigrants representing a wide range of occupations. In that respect, occupational diversity may be just as important as cultural diversity. However, limited data availability necessitates the measurement of diversity in terms of countries of citizenship only.

Effectively our research aims to find answers to three research questions. Firstly, do regions with a greater share of immigrants in the population innovate more? Secondly, what is the impact of the skill composition of the stock of immigrants on innovativeness? Thirdly and finally, does a culturally diverse society form a “contextually-enabling environment” for innovativeness (Glaeser et al. 2010)? We therefore estimate the effects of the share of immigrants in the population, the composition of the immigrant flows and the contribution of immigrants to diversity of the work force on innovativeness of host regions. The econometric estimation exploits a panel of data on 170 NUTS 2 regions in Europe over the period 1991-2001. Innovation outcomes are measured by means of the total number and types of patent applications. Given the geographical concentration and subsequent diffusion of innovation activity, and the spatial selectivity of immigrant settlement patterns, we take account of spatial dependence and of endogeneity of immigrant settlement in the econometric modelling.

The perspective we take is restricted to that of the host country. The extent to which the emigration of highly skilled workers from developing countries (the “brain drain”), impacts on such countries either positively (raising post-compulsory schooling enrolment) or negatively (leading to shortages of workers in education, health, ICT and other knowledge industries) is not considered here, but we note that if a freeing up of the international exchange of skilled labour increases the *global* level of innovation, diffusion of new knowledge may benefit sending nations as well and raise welfare there also (for a review, see Duncan, 2008).

Our results suggest that an increase in the share of the foreign born in the population of a region or an increase in the average skill level of migrants has a positive and statistically significant effect on patent applications. The size of this effect varies between types of patents. Besides migrant share of population and migrant skills, innovation levels are also positively associated with migrant diversity. In Section 2 we provide a brief review of the previous literature on the effects of migration on innovation. The European data set that has been compiled to test for the impact of immigration on innovation is described in Section 3. Various measurement issues are addressed in this section also. Section 4 discusses the methodology and econometric modelling. Section 5 provides a short descriptive analysis. In Section 6 we discuss a range of econometric models that measure the joint impact on innovation of the immigrant share of the population and the skill level and ethnic diversity of the immigrants. Section 7 sums up and suggests avenues for further research.

2. Channels of Influence of Immigration on Innovation

As noted above, there may be many channels through which migration contributes to innovation. In a standard neoclassical setting, the main impact of immigration is distributional (Borjas, 1999). The "immigration surplus" associated with the expanding economy, accruing to the owners of capital and workers who are complements in production to migrants, is quantitatively small. While the associated shift of income from those supplying labour to the owners of capital may be in principal much larger, various adjustment mechanism such as an inflow of capital in an open economy and internal migration may reduce the distributional impacts as well (e.g. Longhi et al., 2010a). However, such comparative static analysis of the impact of immigration ignores the dynamic benefits flowing from new investment, knowledge exchange, greater product variety and consumption externalities associated with the presence of diverse immigrant groups (Ottaviano and Peri, 2006; Bellini et al., 2008).

Population scale and population share effects of immigration result from the fact that immigration boosts local aggregate demand. Such demand is partially met through additional imports, but predominantly through greater levels and greater variety of local production (Mazzolari and Neumark, 2009). While such output growth in the short-run may be met by greater capacity utilization and additional labour supply (predominantly provided by the immigrants themselves), in the long run additional investment will be needed. Such new investment will embody the latest technologies and the associated investment behaviour of firms will encourage product and process innovation. Moreover, the resulting expansion of the host economy may lead to firm growth or additional start-up firms, which will also boost innovation (e.g. Freeman and Soete, 1997). Moreover, by migrants being predominantly attracted to the larger urban areas where job opportunities are the greatest they contribute to urban population growth and increasing population density and thereby strengthen the forces of agglomeration which, as we noted in the introduction, encourages greater innovation.

Given that in the modern knowledge economy technological change is an endogenous process in which the production of new ideas is a function of the number of ideas workers (e.g., Lucas, 1988), the global competition for highly skilled migrants has been intensifying. Moreover, Borjas (1999) argues that immigrants are not randomly selected samples from sending countries. There is a process of self-selection in which the skilled workers who migrate may also be more entrepreneurial and less risk averse (e.g., Kloosterman and Rath, 2003). Additionally, immigration is very selective of age, with the majority of migrants being young adults in their twenties or thirties. Consequently, immigration slows down ageing of the population and the resulting more youthful workforce may be expected to be more innovative (Poot, 2008). Finally, they may also have a considerable ability to adapt to changing circumstances. In sum, their self-selection and the host country entry regulations serve jointly as a *pre-arrival melting pot*. Hence, the second mechanism through which immigration boosts innovation is through the way in which it transforms the local work force.

Probably the main way through which the composition of immigration can make the host economy more innovate is through explicit admission policies that favour highly skilled workers. In the traditional immigrant receiving countries of Canada, Australia and New Zealand the instrument for such policies is a quota system in which visa applicant are given points for favourable human capital attributes, such as education and experience, and those with the highest points are admitted. Additionally, the global mobility of highly skilled workers has been increasing sharply due to globalization, the growing importance of the knowledge economy, and transfers within transnational corporations (e.g., Poot et al. 2008). Professional migrants often make multiple moves over the life course or even commute between multiple residences. This mobility behaviour generates spillover benefits to host countries in terms of transfers of new ideas and work practices that may encourage process and product innovations.

Both historically and at present, the world's greatest cities are inhabited by large and diverse foreign populations.[3] The issue of whether an economy containing such a diverse group of inhabitants is more productive and more creative than a more homogeneous one, is becoming increasingly important. The emerging diversity literature shares roots broadly with the consumption externalities literature (Florida, 2003; Clark et al., 2002; Shapiro, 2003). The main argument is that the amenities offered by cities are a major attraction to highly skilled labour. Florida (2003) draws from this the policy recommendation that cities that aim to develop high-value knowledge-intensive sectors should enhance the local quality

[3] For instance, more than 130 nationalities are represented among the residents of Amsterdam, even though this city only has a modest population of about 800,000.

of life in terms of leisure activities and services they offer to their residents. Such services will also attract various highly skilled immigrants and a concentration of talented immigrants will contribute to boosting economic growth. Of course, the skills of these entrepreneurial people and the city's resources should complement each other to create an enabling environment for creativity (Glaeser et al., 2010). Obviously, the variety of services provided in a city is enhanced by the presence of a culturally diverse society. The seminal work by Jacobs (1969) strengthens this view by emphasizing the importance of economic diversity for an innovative society. Greater diversity promotes diversified information spillovers across production sectors and processes (Glaeser et al., 1992).

Consequently, the third mechanism through which immigration can boost innovation is through generating greater cultural diversity in the host economy. This diversity manifests itself both on the demand side and the supply side. Jacobs (1961) argues that the city is the engine of growth of the economy and immigrants are predominantly drawn to cities. The diversity one finds in cities in terms of the variety of commercial and cultural activities, and the ways in which new ideas and creativity are boosted in diverse urban environments, is highly beneficial for long-run development. City economies are complex, efficient, dynamic, and made up myriad interacting small enterprises. In large cities many of these are run by migrant entrepreneurs, or employ migrant workers. Such enterprises increase the cultural diversity of these cities. This, in turn, encourages the proliferation of new firms and also leads to more innovative behaviour among the local firms. Similarly, firms producing differentiated outputs are also attracted to the large cities. Rapid advancements in technologies have drastically reduced the product life-cycles, which increased the pace of product evolution. These changes encourage firms to locate in agglomerated area, which also attract people from various backgrounds. The benefits of size, density and diversity in large cities yield higher returns to capital. In turn, this encourages new investment and, consequently, economic growth. Scale economies reduce transaction costs in production through generating better labour market matching between available skills and job requirements. The greater availability of heterogeneous skills in the labour market decreases costly job search and imperfect matching. Therefore, complementarities in production yield higher returns to physical and human capital (Quigley, 1998).

However, this does not necessarily imply that increasing diversity is always beneficial. While it can be shown that even in the standard neoclassical model the economic benefits of immigration for the host population tend to be larger, the more dissimilar migrants and native born are (e.g., Borjas, 1999), excessive diversity can increase transaction costs, reduce social capital and lead to social tensions. Bellini et al. (2008) review various studies that suggest that diversity is detrimental to economic growth. Clearly, the relationship between diversity and economic performance in general may have an inverted U-shape. However, in terms of the narrower focus of diversity and innovation a positive, but potentially concave, relationship may be posited.

As noted in the introduction, empirical evidence on the association between immigration and innovation has only emerged in recent years. Patent applications are often used as a proxy for innovation. A common feature of this empirical work so far is a strong focus on North America and highly skilled immigrant populations. We review the US and Canadian evidence first. Hunt and Gauthier-Loiselle (2008) find that high-skilled immigrants boost patenting at the state-level in the US without crowding out native patenting. To control for reverse causality they instrument skilled immigration with an initial share of immigrant high school dropouts. They find that a college graduate immigrant contributes to patenting at least twice as much as their native counterpart does. This is clearly related to the disproportionate share of immigrants in the fields of science and engineering in the US. Chellaraj et al. (2008) use US time series data to show that an increase in foreign students raises patent applications; and more so than an increase in skilled immigration. A similar finding is also reported by Hunt (2009) by means of the 2003 US national survey of college graduates. Hunt (2009) emphasizes that migrants who enter with student or trainee visas have better outcomes in wages, patenting, commercializing and licensing patents than native college graduates. Kerr and Lincoln (2010) and Kerr (2010) use an exogenous surge in the immigration of scientists and engineers in the U.S., due to the 1990 Immigration Act, as the means to identify the impact of immigration on the level and spatial patterns of US innovation. Especially the increase in Chinese and Indian patenting, referred as 'ethnic invention', has a strong correlation with admissions of foreigners by the H-1B type of visa in the US.

Zucker and Darby (2007) focus on the geographic movements of "star scientists" in the US and other countries that are ranked high in science and technology (S&T). They find a link between their movements and innovative activity in receiving countries and regions. Star scientists, many of whom are foreign born, tend to cluster in particular places that also attract high-tech firms, and have a strong incentive and ambition to commercialise innovations. Zucker and Darby conclude that return migration and fewer opportunities for gifted students to remain in the US after graduation may be detrimental to firm start-up and growth in the S&T sector in that country.

Partridge and Furtan (2008) find that skilled immigrants from developed countries boost patenting in the provinces of Canada. They find that a 10% increase in immigrants with a sufficient level of language proficiency increases the provincial patent flow by 7.3% in Canada. Particularly immigrants with backgrounds from Western Europe and North America have such an impact. This highlights the importance of communication skills, as well as complementarities between immigrants and natives. Maré et al. (2010) use surveys of innovation activity reported by New Zealand firms (both product and process innovations) to check for a link with the presence of immigrants and find that such an association exists at a broad spatial scale (labour market areas) but not at the level of local neighbourhoods in that country.

Niebuhr (2010) shows how cultural diversity (in terms of workers' nationalities) boosts patent applications across German regions. She uses the geography of prior immigration patterns as an instrument to identify the causal effect. Finally, Lee and Nathan (2010) use a 2007 survey of London businesses and find a significant positive relationship between cultural diversity of the workforce of these firms and innovation. The review of the available studies suggests that there is widespread, but not always robust, evidence of a positive link between immigration and innovation. Moreover, as noted earlier, this linkage has been rather under-researched in Europe. The present paper aims to fill this gap.

3. Data and Measurement Issues

The major source of the data used in this study is Eurostat's *General and Regional Database.* The 12 European countries are included in our dataset are: Austria, Belgium, Denmark, France, Germany (western), Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden and United Kingdom. The dataset contains information on 170 regions in those countries over a period of 11 years, starting in 1991. It consists of four sets of indicators: (i) patent applications, (ii) population & labour force, (iii) immigration, and (iv) production structure & performance (See Table 1).

The available data have several limitations. Firstly, data on patent applications to the European Patent Office (EPO) by regions are available *only* at NUTS 2 level.[4] This limited the analysis to this level, even though some regional information is available at the NUTS 3 level. Consequently, where data were only available at the NUTS 3 level, such data had to be aggregated to NUTS 2 level. The aggregation proved to be very time consuming as the coding and classification of NUTS 3 regions have changed over time.

There are two major branches of patent data, namely patent applications to the EPO by IPC (International Patents Classification) sections (with eight sub-sections), and by high-technology fields (with three sub-sections).[5] We consider both the aggregate of all patents

[4] The Nomenclature of Units for Territorial Statistics (NUTS) is a geocode standard for referencing the subdivisions of European countries for statistical purposes. The NUTS 1 level refers roughly to states or large regions, level 2 to provinces and level 3 to counties.

[5] We use the EPO International Patents Classification (IPC) data to measure the patent applications per million inhabitants by priority year. The priority year refers to the first filing worldwide. This is therefore the year closest to the invention date. The total patent applications per million inhabitants used in this study consist of two large patent sub-groups, namely the IPC sections and High Technology Patents sections. The sub-categories of these two broad groups are as follows: IPC Sections: a) Human necessities, b) Performing operations; transporting, c) Chemistry; metallurgy, d) Textiles; paper, e) Fixed constructions, f) Mechanical engineering; lighting; heating; weapons; blasting, g) Physics, h) Electricity. High Technology Patents Sections: a)

and the various sub-sections. Patent applications are regionally allocated according to the inventors' place of residence. If there is more than one co-inventor, then a patent count will be equally divided by the number of inventors, which implies that fractions of a patent may be assigned to different regions and/or countries. This eliminates multiple counting and avoids overestimation of the importance of some regions as being the main generators of patent applications. The inventors of these patent applications are obviously not exclusively immigrants and the dataset includes both non-native and native applicants. [6] Given the fact that patent applications require a costly and time-consuming registration process, researchers face three major problems when using patents. Firstly, patent application procedures, which are determined by each country's central government, may vary substantially between different countries (Furman et al., 2002). Secondly, the propensity to register innovations may be culturally dependent. Thirdly, it is questionable that the residential location of the patent applicant always corresponds with the region where the impact is felt the most strongly.

The literature provides a range of theories on the geography of innovation, ranging from incubation theory to product life-cycle theory and diffusion theory (e.g., Davelaar and Nijkamp, 2004). Nonetheless, there is broadly consensus on the local determinants of innovation production (Gordon and McCann, 2005). For instance, the demographic structure of the local population, and the information and institutional infrastructure drive the innovative potential of localities. Since innovations are indicators of the creativity of society, and have an economic value in terms of their impact on economic growth, considerable effort has been devoted to proxy visible innovations by means of patent applications or research grants. As a result of different classifications and intrinsic variability, it is well accepted that patents are an imperfect proxy of innovation, although this would actually depend on the research task (Griliches, 1990).

Another data limitation is that, although many variables are available annually for the period of 1990-2005, the 'share of foreigners in the population' data are available in some countries *only* in 1991 and 2001 from population censuses.[7] Moreover, the share of

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High Tech: Total high tech, Computer and automated business equipment, Micro-organism and genetic engineering, Aviation, Communication technology, Semiconductors, Laser. b) ICT: Consumer electronics, Computer-office machinery, Telecommunications, other ICT, total ICT.c) Biotechnology.

[6] Although the patent applications database gathered from the Eurostat website is fairly complete, there are some missing values for the UK and some other countries. Such values were imputed through interpolation by means of compound growth rates of patent applications. Also, in some years in some regions patent applications were zero. Given the use of the natural logarithm of patents as the dependent variable, patent activity was imputed in those cells at a non-zero level that is smaller than the smallest value in the number of patent applications in the given dataset. Effectively zeros in the matrix of patent applications were replaced by total patent applications per million inhabitants being 1.03.

[7] The data for 1991 were kindly provided by Giovanni Prarolo at the NUTS 3 level. German data on the share of immigrants by citizenship is available only for western Germany and the 2001 data were provided by IAB Nuremberg, using information from the social security administration. The data refer to people who are active in the labour market, but not to their families. An estimate of the foreign born population is obtained by

foreigners in the population could only be disaggregated by country of citizenship at the NUTS 2 level in 2001. Furthermore, no information was available on the skill levels of the immigrants at NUTS 2 level, so we use the country of citizenship information as a proxy for the skills and the influence of culture that are specific to the country of citizenship. This is appropriate where the available data at the national level allows us to categorise immigrants in groups that are known to be predominantly skilled or unskilled. We created five major categories (Africa, America, Asia, Europe, and Oceania) as well as broader regional categories within the continents (e.g. North-America, North-Africa, Middle East and Central and Eastern European (CEE) countries).

No information is available on time the immigrants have spent in the host country or region, the skills acquired in the process of integration to the host country, or on the number of foreign born migrants who were subsequently naturalized. We aim to measure the diversity effect of immigrants on the innovativeness of the host regions by means of a fractionalization index that is calculated on the basis of the regional population by country of citizenship.[8] However, since the population by country of citizenship dataset is available only in 2001, we cannot account for a change in diversity over the 1991-2001 period.

Data on human resources in science and technology as a percentage of the active population aim to measure the stock of aggregate knowledge in the regions, which acts as the major input in the production of new ideas. GDP per capita in purchasing power parity is used as an indicator of the ability of regions to convert the available knowledge into economic value (Furman et al., 2002). In general, the share of GDP devoted to R&D spending is quite constant over time, and often increasing with the development level of the region. Given that R&D spending per capita in a region is endogenous; GDP per capita is a better measure of the resources that are available to the knowledge industries rather than R&D expenditures themselves (Hunt, 2008; Kleinknecht et al., 2002).

The size of a region's population and its density are commonly used variables to account for the impact of agglomeration on innovation. Average population size captures the available resources, the scale of production of non-traded goods and services, and the market size of the regions. Population density measures the likely intensity of knowledge spillovers (Carlino et al., 2007). We also obtained data on the ratio of the value added of services over value added of the industrial sector in a region. We expect this variable to have a negative effect on patent applications, because patents are disproportionately generated in the high-end manufacturing sector.

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dividing the number of foreign-born workers by the regional labour force participation rate. This estimate of the foreign born population in each German region is then used to calculate the share of immigrants in the population.

[8] A major limitation of our measure of diversity is the absence of comparable data on the linguistic or ethnic diversity of the European regions. It is possible to extract some ethnic and linguistic diversity information from various sources mentioned in Alesina et al. (2003) but this information is available only at country level.

A final issue of importance is that of accessibility. Clearly knowledge spillovers require face to face interaction and the cost of travel between the various innovation clusters is likely to matter. The accessibility index used in this study was provided by ESPON.[9] The theoretical assumption behind potential accessibility is that the attractiveness of a destination increases with the size of the population and decreases with distance, travel time or cost. These aspects are combined multiplicatively to calculate the potential accessibility:

$$A_i = \sum_j W_j^{\alpha} \exp(-\beta c_{ij}) \tag{1}$$

where A_i is the accessibility of area i, W_j is the opportunity (population) to be reached in area j, and c_{ij} is the generalised cost of reaching area j from area i. A_i is the total of the activities reachable at all areas j weighted by the ease of getting from i to each area j. The interpretation is that the greater the number of attractive destinations in areas j is and the better areas j are reachable from area i, the greater is the accessibility of area i. In turn, the generalised cost c_{ij} is calculated as follows:

$$\bar{c}_{ij} = -\frac{1}{\lambda} \ln \sum_m \exp(-\lambda c_{ijm}) \tag{2}$$

where c_{ijm} is the cost of travel by mode m between i and j, and λ is a parameter indicating the sensitivity to travel cost. This formulation of composite travel cost is superior to average travel cost because it makes sure that the removal of a mode with higher cost (i.e. closure of a rail line) does not result in a - false - reduction in aggregate travel cost (ESPON, 2009).

The information on all variables is summarised in Table 1. With respect to diversity, the voice that this may have significant economic benefits has become stronger in recent years.[10] Since the turn of the millennium, several studies provide fairly robust results between innovation and diversity, starting with Duranton and Puga (2000). Diversity and cultural coherence evolve over time and through interactions between people and places. In order to measure the impact of cultural diversity on an economy, we need to acknowledge that diversity is a multi-layered concept in which ethnic, linguistic, religious and personal perceptions of belonging overlap. Among these, ethnicity may be considered a general concept which is formed by common culture and ancestry. The other dimensions such as language or religion are sub-types of ethnicity (Wimmer, 2008). Unfortunately, Eurostat data do not permit us to make such distinctions at the NUTS 2 regional level.

[9] See ESPON (2009).
[10] A good example is Page (2007). See also the review of this book by Ioannides (2010).

The diversity effect is measured by means of the fractionalization index (Alesina et al., 2003), which is calculated as follows:

$$Div_j = \qquad (3)$$

in which s_{ij} is the share of the group i (i=1, ..., N) in region j.[11] The index represents the probability that two individuals randomly selected from a sample will belong to different population groups. The minimum value of the index is 0 (complete concentration in one type) and the maximum value is 1-1/N. The natives are excluded from the diversity index calculations because diversity in the form of having immigrants present is already captured by the share of immigrants in the population.

4. Methodology and Econometric Modelling

The nature of the data, a pooled cross-section time-series panel of regional average characteristics, suggests that panel data techniques that account for heteroscedasticity, endogeneity and spatial spillovers are the most appropriate. Where panel models are employed, both fixed and random effects specification are considered. However, the availability of data on the share of foreigners at only two points in time (1991 and 2001) and data on the diversity among these immigrants at only one point in time (2001) limit the extent to which dynamic panel models can be utilised. Given that the data refer to regional averages rather than a random sample of individuals, the fixed effects model is both theoretically preferred and also confirmed by means of the Hausman test, but when we estimate a dynamic panel model of 11 years of patent applications (1991-2001), with the interpolated share of foreign residents added, or the diversity index, we are restricted to the random effects panel model with AR(1) error. Consequently, we devote most attention to specifications that take a longer time frame per observation, namely two pooled cross-sections of average patents (1991-1995 and 2001-2005). This way we are also able to avoid the issue of having to specify serial autocorrelation in the presence of missing annual immigration data across. Arguably, the longer time frame is also theoretically preferable since the impact of immigration on innovation is unlikely to manifest itself fully within a year (Griliches, 1990).

Hence, the basic specification is as follows:

$$\ln P_{i,t} = \mu_i + \mathbf{m}_{i,t}'\gamma + \mathbf{x}_{i,t}'\beta + \varepsilon_{i,t} \qquad \varepsilon_{i,t} \sim \mathrm{N}(0, \sigma^2_i), \qquad (4)$$

[11] Alternatively, the fractionalization index is defined as 1–H, with H the Herfindahl index of concentration of observations in certain categories of a classification.

where $P_{i,t}$ refers to average patent applications per million inhabitants in region *i* in period *t*, $\mathbf{m}_{i,t}$ is the vector that measures the characteristics of immigration in the region, $\mathbf{x}_{i,t}$ is a vector of control variables, and μ_i captures regional fixed effects, and $\varepsilon_{i,t}$ is the error term.

As motivated earlier in the paper, there are five ways in which immigration can influence patent applications. They are the population scale effect, the population density effect, the share of foreigners in the population, the skill composition of the migrant flow and the diversity of immigrants (measured by their countries of citizenship). Given the limitations of the data, we can only account for the varying skill levels of immigrants by grouping migrants on the basis of broad regions within the continents they came from.

An important problem in measuring the impact of immigration on innovation is the presence of two-way causation. Immigration is likely to be endogenous. Particularly skilled migrants may be attracted to regions where per capita income is growing, where there is considerable R&D activity and patents applications are likely to be increasing as well. We will use instrumental variables estimation to deal with a possible endogeneity bias. We therefore instrument the share of foreigners by an exogenous variable. The instrument needs to be correlated with the share of foreigners in the regions, but not with the error term of the model that explains the spatial and temporal variation in patent applications.

The literature review suggested that commonly used instruments are historical migration patterns, the initial share of immigrant high school dropouts or one-off major changes in migrant admission policies. Here we propose a novel spatial instrument that has not been previously used. For this, we searched for a company that has ubiquitous establishments, but whose innovation is largely non-spatially differentiated. The company must determine the location of new outlets predominantly on the basis of population density rather than income (given the correlation between income and R&D activity). [12] The obvious candidate is the distribution of McDonald's restaurants across NUTS 2 regions. Unlike in North America and in some other parts of the world, McDonald's restaurants are considered in Europe a symbol of cosmopolitanization rather than simply a caterer of fast food to low income people. The choice of McDonald's as an instrument fits in with the consumption externalities literature. The chain is associated with a life style that is internationally connected and aims to serve a variety of people. McDonald's is also a significant employer of unskilled migrants. Consequently, a higher number of McDonald's restaurants may be used a proxy for the openness and international connectedness of regions. On the other hand, the location of McDonald's restaurants is not in any way driven by patenting. Formal tests showed that the spatial distribution of McDonald's restaurants turned out to be a strong instrument that explains about 20% of the cross section variation in the share of foreign residents.

[12] Opening new restaurants in the highly populated areas, but not necessarily high GDP areas, is also mentioned as a location choice strategy in the frequently asked questions section of the McDonald's UK's website.

The data were collected from the McDonald's country websites by using regional locators that provide the addresses of the restaurants closest to the specified locality. Given the larger concentration of McDonald's restaurants in large population areas and population scale being already a variable in the model, we adopt the number of McDonald's restaurants per million inhabitants as the instrument. This weighting scheme therefore becomes an exogenous index of the extent of cosmopolitization and culturally openness of the NUTS 2 regions.

Besides the issue of endogenous regressors, pooled cross-section time-series of regional outcomes should also take into account the possibility that the error term of the regression model is spatially correlated. There is a vast literature that argues, and provides evidence, that there are spatial knowledge spillovers, and that spatial proximity matters (Döring and Schnellenbach, 2006). Although it can be argued that the flows of knowledge and ideas are invisible (Krugman, 1991), proximity may lead to more exchange. Consequently, patent activity in any given region will be positively affected by patent activity in surrounding regions. Spatial econometric techniques are applied to incorporate the various spatial interactions that may exist between the regions in terms of innovation. We use a row standardized spatial weight matrix, with weights inversely proportional to the Euclidean distances between the centres of the regions. Before we report the results of both non-spatial and spatial econometric modelling in Section 6, we first provide some descriptive in the next section.

5. Descriptive Analysis

The number of patent applications per million inhabitants of NUTS 2 regions per year has more than doubled from 55.8 in 1991 to 121.9 in 2001. The distribution across the 170 regions is given in Figure 1 for each year from 1991 until 2001. Many of these patent applications fall into the ICT sub-category. The distribution across the sub-categories is displayed in Figure 2.

There were 26.7 million immigrants (foreign citizens) living in the EU12 area in 2001. They represented 7.2% of the total EU12 population. The mean (median) share of immigrants in the population across the 170 NUTS 2 regions increased from 5% (3.8%) in 1991 to 7.2% (6.0%) in 2001. In comparison with the traditional immigrant-receiving countries of North America and Australasia, the percentage foreign born is still relatively small in many European regions. Nevertheless, there has been a relative shift of the distribution of immigrants from Western Europe to Central and Southern Europe. In recent years, the latter countries have attracted a disproportionate share of new immigrants.[13] Figure 3 presents the distribution of the share of foreigners by NUTS 2 regions in 2001. The average across the EU12 regions (7.2%) is also shown in this figure.

Table 2 provides descriptive for the two five-year period averages that constitute most of the analysis. Patent applications range from 0.2 to about 727 per million population. The share of foreigners ranges from 0.1 percent to 28.6 percent of the population. The diversity (fractionalization) index has an average value of 0.494, with a range from 0.185 to 0.781.

Our analysis period coincides with the fall of the Berlin Wall as well as the war years in the Balkans. Until 1997 some countries, especially Germany, continued to welcome CEE (Central & Eastern-European countries) migrants with bilateral agreements to fill a gap in the labour market. Other western countries implemented soon after the fall of the Iron Curtain restrictions in mobility from the CEE and Balkan countries. However, 'a migration surge from these regions that followed established ethnic networks' was nonetheless observed towards the West (Straubhaar, 1999). Besides this network effect, other two important drivers have played a role in the migration decision: geographic and linguistic proximity. The language skills have been a crucial factor in the choice of destination (Fassmann and Hintermann, 1997). There were relatively large migration movements from the aforementioned countries to Germany and Austria over the study period. Geographical proximity has also been a major factor in migration decision. In a survey of 4000 people from the four largest countries of CEE[14], 48% of the respondents considered geographical proximity important and 43% of those considered presence of friends/relatives in the destination country central to their migration decision. We are unable to separate out in our measure of high-skilled workers in the NUTS 2 regions those who are migrants, but several studies emphasize the inflow of substantial number of high skilled immigrants from CEE countries (Wolburg 1997: 32).

EU citizens living in another EU country than their country of origin make up the largest share (about 72%) of all foreigners in the EU12 (see Table 2). Africans are the next largest group, followed by Asians and Americans. Internal mobility within the EU12 is only about 2.2% in the study period (Peri, 2005). The five regions with the highest share of foreigners are shown in Table 3. They represent London, Brussels, Paris and Vienna. In these cities one fifth or more of the inhabitants have been born in another country. Table 4 shows that while London is also the city with the highest value of the diversity index, there are also some regions with a high diversity index despite a small share of foreigners in the population (NE Scotland, East Anglia and Berkshire, Bucks and Oxfordshire). Note that these regions include

[13] For instance, the foreign-born share in Vienna, Austria, became one of the highest (see Table 3), while in Spain the share of immigrants increased from 0.1% to 5%. Similarly, Italy experienced an increase from 0.1 % to 4% over the same period.

[14] Czech Republic, Slovakia, Poland, and Hungary.

the universities of Edinburgh, Cambridge and Oxford respectively). Table 4 also shows that some regions with a high share of foreigners have at the same time a low diversity index, because their migrants are predominantly from within Europe (Austria is an extreme case). Even where immigrants come from different parts of the world, immigrants may be highly concentrated across a few source countries. For instance, despite immigrant having a large share of the population, almost 40% of the immigrants in Germany originated just from two sources (Sudekum, 2009).

The scatter diagram in Figure 4 clearly shows the positive relationship between patent applications and the share of foreigners. Linear regression lines are also presented. These show that the slope of the relationship has increased between 1991 and 2001 (the correlation coefficients are 0.33 and 0.48, respectively). However, it is clear from the 2001 values that the highest patent applications are not necessarily in the regions where the share of immigrants in the population is the highest. In any case, immigrants are not homogeneous and those regions with the highest level of patent applications may be regions where the share of highly skilled migrants in the population is the largest, even though the overall share if immigrants may be relatively low. Moreover, as patent applications increased over time they also became more dispersed. In 1991 innovation activity was still highly concentrated in particular regions, yet spin-offs from traditional patent producing regions resulted in innovation activity becoming more widespread in the EU12 by 2001 (see Figure 5). In the following section, we discuss our findings from multivariate analysis.

6. Regression Results

Standard specifications

Table 5 presents the results of three specifications of the random effects panel model. [15] Specifications I, II and II test the density effect, the skill composition effect and the diversity effect of migration on innovation respectively. We control in all three models for time and country effects to capture the influence of national institutions and trends. Robust standard errors are calculated to control for cross-sectional heteroscedasticity.

Specification I suggests that a 1 percentage point increase in the share of foreigners increases patent applications by 0.23%. The positive effect of immigrants on the innovativeness of the regions is statistically significant at the 1% level. Similarly, a 1% increase in GDP per capita leads to a 1% increase in patent applications. Average population size is a commonly used proxy for measuring the agglomeration, demand and consumption potential of the regions. Our findings show that a population increase by 1% increases

[15] All calculations have been carried out with Stata 11.

patent applications by 0.30%. Both the income per capita and population scale effects are statistically significant at the 1% level. As expected, the ratio of services over manufacturing value added has a negative effect on patent applications. This effect is also significant at the 1% level. The coefficient of the stock of human resources in science and technology is insignificant, although it has the expected (positive) sign. The country-level dummy variables (not shown in Table 5) show that patent applications are particularly high in The Netherlands and low in all Mediterranean countries.

Specification II in Table 5 shows how the composition of the immigrant population, in terms of their nationalities, contributes to the innovation output of European regions. We imposed the same model as before, but replace the share of foreigners by variables that measure the shares of various continents in the distribution of the migrant nationalities. Regions that have relatively many migrants from North America (who are likely to be highly skilled) have a positive impact on the number of patent applications. In contrast, regions with many migrants from Asian countries have relatively fewer patent applications. The coefficients of the other variables are roughly similar as in Model I. All statistically significant variables are significant at the 1 percent level. An additional variable introduced in Model II is the accessibility index. It is clear that innovation activity is greater in the European regions that are more accessible.

Specification III tests the influence of ethnic diversity of the regional population. The coefficient of fractionalization index is positive, which suggest that there are positive externalities in the form of greater innovation activity associated with culturally more heterogeneous societies. Our measure of diversity in the 12 European countries has a statistically significant effect on the patents applications.

We noted earlier in the paper that annual observations may not be the appropriate unit of measurement for considering the impact of immigration on innovation. Consequently, we also consider how the share of foreigners in a year influences innovation activity in the subsequent five years, by using five year averages of the variables that were included in the specifications reported in Table 5. This approach also provides a possibility to control for business cycle effects, which are likely to have an influence on patent applications. In this set up, the fixed effects panel model is preferred. Table 6 presents the results of this model and OLS estimation of the effect of diversity and migrant source regions (which are only observed in 2001). All specifications test for the population scale effect and column (1) also for the density effect by means of the fixed effects (areas) of the NUTS 2 regions. The equations test furthermore the migration share effect (column 1), the skill composition effect (2), the diversity effect of migrants on innovation (3), and the joint density and diversity effect of immigration (4). In all four models we account also for time and country effects to capture the influence of national institutions and trends. The estimations also include again controls for GDP per capita, regional specialization in services/industry, and stock of human capital in S&T fields in the regions.

Specification I reports again a positive association between higher density of foreigners and patents applications, somewhat smaller but similar to that in Table 5. The effect size is significant at the 1% level. In the fixed effects panel model estimation, the time dummy captures a high share of time-variant effects (namely patents have grown in most regions), while cross-section variation seem to be much less.

The share of migrants from various backgrounds may have different effects in line with the concentration of foreigners in particular localities, i.e. the effect may be nonlinear. To allow for this we classified the foreigners' share in regions by one and two standard deviations from the pooled mean share, which is 6%. We are particularly interested in the category where the share of foreigners is greater than 11% and that corresponds about 11% of the observations in the structural equation. That group includes regions like Brussels, Ile de France, Vienna etc. The re-estimated version of column (1) in Table 6 shows that the effect sizes on patent applications increase with the share of immigrants up to 15%, and then it starts to fall. Clearly, the migrant share effect on innovation is non-linear.

Specification (2) in Table 6 shows again how the composition of the immigrant population, in terms of their nationalities, contributes to the innovation output of the European regions. We were also able to disaggregate the immigrants by narrower groups within the continents (North Africa, other African countries, America, Middle East, East-Asia, CEE, other European countries, Oceania, Other). We find a significant effect for immigrants from America, (South) Africa, and CEE.

Specification (3) tests the influence of ethnic diversity of the regional population. The coefficient of the diversity index is again positive, but somewhat smaller than in Table 5. Almost all the covariates are significant at least at 5% level, meaning that even after controlling for the effect of various factors that boost innovation the positive contribution of diversity survives, hence diverse society enhances creativity of the regions. An important discussion in the literature is on how much cultural diversity is beneficial on the economic growth. We present an empirical experiment to shed light on the expectations about the relationship between cultural diversity and economic growth. We measure this relationship by including the quadratic form of the diversity index into the structural equation (See Specification 2 in Table 9). In Figure 6 we indicate the estimated effect of diversity in equal intervals from the mean value of the composite diversity index. The large point stands for the estimated effect size at mean value. It is shown that indeed there is an optimal point for the benefits from cultural diversity. In the right-tail of the graph it is possible to see that the positive effect of diversity is lessened. The last interval includes the most diverse and highly populated regions in our sample. A crucial aspect to be emphasized is that inverted U-shape occurs *only* when the natives are also added in calculation of the diversity index. Once natives are left out we observe that the gains from a small amount of diversity are not positive until the optimal level of having diverse population within a particular area is reached. After this point, the impact of diversity becomes increasingly positive (see Figure 6).

Finally, we address the joint effects of diversity, the migrant share effect of immigrants and skills composition on patent applications (See column (4) of Table 6). As a skills indicator, we focus on the American migrants, given that they are known to be a pre-dominantly high skills group in Europe. The result shows the strong positive impact of both diversity and migrant share effects on patent applications and the presence of American migrants.

Controlling for potential endogeneity

Table 7 reports the results of the 2SLS estimations of the FE model. The specification tests reports the *density* (relative to population) of McDonald's restaurants as a strong instrument (F-test > 10) with an explanatory power of about 20% of the cross-section variation of the share of foreigners in regions. The diagnostic tests confirm the exogeneity of the instrument. The results tell a qualitatively similar story. It is noticeable that the impact of immigration on innovation activity has become quantitatively larger and still significant at 1% level. The IV estimation suggests a stronger effect of the presence of a higher share of foreigners on increased levels of patent applications. The estimation with the cultural diversity index reveals similar results to that of Table 6, but the coefficient is smaller. The other control variables are mostly significant with the expected signs for the coefficients. In particular, as theoretically expected, the variable on the human capital stock of the regions is highly significant and positively correlated with patents. Therefore, our results are robust to previous findings.

Spatial econometric analysis

Agglomeration economies, knowledge spillovers and the role of proximity suggest that spatial effects in innovation are important. We generally expect that diffusion of technology is faster among regions that are close to each other. This effect may result from a supply-side externality (Vaya et al., 2004). Moreover, omitted spatially correlated exogenous variables and random shocks coming from neighbouring regions may influence the outcomes of regions in close proximity (Fingleton and Lopez-Bazo, 2006). Hence, we will account for spatial autocorrelation by re-estimation of Table 6 by means of spatial econometric models.

It is a common practice to use spatial weight matrices that are based on the pair-wise distances between the cross-section units to detect spatial correlation in the error term, while spatially lagged interdependence is more a matter of socio-economic relationships. The spatial weight matrices specify a form of proximity or similarity (Larch and Walde, 2008). As noted earlier, we calculated a row-standardized spatial weight matrix where we used the Euclidean distances between the centres of the regions. The results of the Moran's *I* statistics calculated by means of the OLS equivalent of Model II, across 266 NUTS 2 regions suggests the presence of strong spatial autocorrelation in innovation modelling. Five tests have been performed to assess the spatial dependence in the model. In the presence of spatial autocorrelation the choice of the econometric specification is based on the statistical significance of the test statistics (Florax and de Graaff, 2004). Given heteroscedasticity of the errors in the model, the robust tests preferred. The robust Lagrange multiplier test indicates the presence of spatial autocorrelation in the error terms and the null hypothesis that the $\lambda=0$ is rejected at the 5% level (LM: 6.095, p-val.: 0.014). The existence of spatial correlation in the error component, suggests that independence of the observations is violated.[16] An omitted variable bias due to the omission of a spatially correlated unobserved effect from neighbouring regions may lead to erroneous estimations.

Table 8 summarizes the results of the estimations incorporating the spatial dimensions. Estimation with the pooled data on five year averages by the spatial error model generates coefficients that are highly significant, and slightly higher (0.209) than the one reported for the fixed effects panel model (0.155) in Table 6. Concerning the estimations with the diversity index, the results confirm the robustness of the previous findings. The effect size is similar and significant at 1% level. The coefficients of the industrial composition and stock of human resources in science and technology variables have become very positive and significant at 1% level, stressing their importance on patent applications.

7. Conclusion

This paper discusses the various effects of immigration on innovativeness of the regions. We estimated four different effects (and implicitly a density effect as well) that might occur as a result of increasing number of foreigners in particular locations. We specifically considered for population scale, migrant share, the skills composition and diversity effects of foreigners. To address various econometric issues such as omitted variable bias, endogeneity and spatial dependence, robustness checks were conducted through instrumental variables and spatial autocorrelation estimations.

[16] The spatial error model estimates the following equations under the assumption that there may always be spatially correlated measurement error in the estimations, since one cannot model all the aspects of a region, e.g. the boundaries, natural resources, climate of study areas may not overlap with the NUTS 2 areas.
$\mathbf{y} = \mathbf{X\beta} + \boldsymbol{\varepsilon}$, $\boldsymbol{\varepsilon} \sim N(0,\sigma^2)$; $\boldsymbol{\varepsilon} = \lambda\mathbf{W}\boldsymbol{\varepsilon} + \nu$, λ is spatial lag autoregressive parameter, $\mathbf{W}$ is a spatial weight matrix and $\mathbf{v}$ are independently distributed errors.

The econometric results of this paper are supportive of the view that Jacobs' externalities are important. In other words, cross-fertilization of ideas in a diverse urban environment creates a contextual environment where more ideas are produced and turned into innovative outputs. The regions with many immigrants have a positive association in production of higher number of patent applications. Moreover, diversity of abilities brought by the immigrants may be beneficial and complementary to the native workers in the host regions. The varying degrees of cultural differences in terms of horizontal differentiation create opportunities for culturally diverse regions. However, we also reported that there is an optimal value for the benefits that may be extracted from diversity because the benefits gained from diversity appear to decrease with a value of the fractionalization index that exceeds 0.200.

Higher competitiveness and availability of knowledge spillovers in a culturally diverse setting contributes to the innovativeness of the regions in Europe. We found that particular immigrant groups have more positive and significant effect on patent applications; however we would need better data for in-depth research to conclude how a variation in composition of the immigrant flow may affect the economic output on the host economy.

The robustness checks confirm the validity of our estimates and also the causal direction of the relationship, that is, from immigrants to innovativeness of the region. The spatial econometric analysis corrected for the spatial autocorrelation due to omitted variable bias of spatially correlated and unobserved effects.

We had considerable data availability problems at the regional level that impede us to pursue more comprehensive research on this topic. In future research we plan to conduct the analysis at the micro level, combining firm data on innovation with matched data on employee characteristics. Such research will be helpful to designing immigration policies that are targeted to ensuring the best economic and social outcomes. Such targeting based on perceived host country outcomes is already the main motivation for the points systems that are used to select skilled migrants in Australia, Canada, New Zealand and the United Kingdom.

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Table 1: The available data

	Indicators	Code	Measures	NUTS	Years	Datasource
1	**Patent applications**	p	Total patent applications per million inhabitants (pmi)	nuts2	1990-2005	Eurostat, EPO
		ht	High-technology patent appl. pmi	nuts2	1990-2005	Eurostat, EPO
		ict	ICT patent appl. pmi	nuts2	1990-2005	Eurostat, EPO
		bio	Biotech patent appl. pmi	nuts2	1990-2005	Eurostat, EPO
		e	Electricity patent appl. pmi	nuts2	1990-2005	Eurostat, EPO
		fc	Fixed constructions patents pmi	nuts2	1990-2005	Eurostat, EPO
		ph	Physics patents pmi	nuts2	1990-2005	Eurostat, EPO
		mec	Mechanical engineering patents pmi	nuts2	1990-2005	Eurostat, EPO
		tx	Textiles and papers patents pmi	nuts2	1990-2005	Eurostat, EPO
		hn	Human necessities patents pmi	nuts2	1990-2005	Eurostat, EPO
		pot	Performing operations; transporting patents pmi	nuts2	1990-2005	Eurostat, EPO
		c	Chemicals patent	nuts2	1990-2005	Eurostat, EPO
2	**Population & labour force**	ave	Average population of the calendar year	nuts3/nuts2	1990-2006	Eurostat
		pd	Average population divided by total area of the region	nuts3/nuts2	1990-2006	Eurostat
		hr	Human resources in science & tech. as a share of active population	nuts2	1994-2007	Eurostat
3	**Immigration**	shfor	Share of foreigners in total pop.	nuts3/nuts2	1991, 2001	Eurostat, IAB, Censi
		div	Fractionalization index = 1-Herfindal index of nationality shares	nuts2	2001	Own calculations
4	**Production structure & performance**	smv	Service sector value added divided by industry sector value added	nuts3/nuts2	1990-2008	Oxford econometrics
		gdp	GDP per capita in PPP (Adjusted to EU25=100)	nuts3/nuts2	1990-2005	Oxford econometrics
5	**Geography**	w	Weight matrix based on Euclidean distance	nuts2	-	ETIS
		mcd	Number of McDonald’s restaurants	nuts2	2009	Own calculations
		access	Accessibility index	nuts2	2009	ESPON

Table 2: Descriptives – 170 NUTS 2 regions, 1991-1995 and 2001-2005

Variables	Obs	Mean	Std. Dev.	Min	Max
Patent applications per million population*	340	90.530	101.849	0.212	727.544
Share of foreigners in 1991 and in 2001 pooled	340	0.060	0.043	0.001	0.286
Ratio of services over industry value added*	340	2.779	1.209	0.847	11.026
GDP per capita*	340	109.518	33.181	10.800	384.400
Population*	299	2,005,932	1,703,171	116,270	11,300,000
Human resources in S&T as % of active pop.*	334	32.179	7.530	11.540	55.286
Area of regions (km^2)	340	14,748	18,999	161	154,000
McDonald’s restaurants per million pop.	340	13.499	7.086	0	33.6
Diversity index in 1991	340	0.494	0.170	0.185	0.781
Fraction of Africans among foreign citizens in 1991	340	0.099	0.072	0.003	0.304
Fraction of Americans among foreign citizens in 1991	340	0.066	0.084	0.003	0.437
Fraction of Asians among foreign citizens in 1991	340	0.098	0.116	0.004	0.568
Fraction of Europeans among foreign citizens in 1991	340	0.717	0.187	0.232	0.971
Fraction of Oceanians among foreign citizens in 1991	340	0.002	0.005	0.000	0.037
Fraction of Others among foreign citizens in 1991	340	0.017	0.028	0.000	0.211
Fraction of North-Africans among foreign citizens in 1991	340	0.056	0.065	0.001	0.294
Fraction of Other-Africans among foreign citizens in 1991	340	0.043	0.045	0.002	0.275
Fraction of Middle-Eastern people among foreign citizens in 1991	340	0.012	0.013	0.000	0.055
Fraction of Asia-others among foreign citizens in 1991	340	0.086	0.110	0.004	0.551
Fraction of Central & Eastern Europeans among foreign citizens in 1991	340	0.070	0.084	0.003	0.387
Fraction of Other Europeans among foreign citizens in 1991	340	0.647	0.184	0.211	0.901
Fraction of Natives among foreign citizens in 1991	340	0.931	0.041	0.728	0.984

* The individual observations are the average values for the period 1991-1995 and for the period 2001-2005 for each NUTS 2 region.

Table 3: Regions with the highest and lowest share of foreigners (*shfor*)

2001	NUTS 2 Codes	Regions	Share of foreigners
Regions with highest shfor	UKI1	Inner London	0.333
	BE1	Brussels	0.272
	UKI2	Outer London	0.227
	AT13	Wien	0.236
	FR10	Il de France	0.180
Regions with lowest shfor	UKD1	Cumbria	0.022
	ITG2	Sardegna	0.019
	BE25	Flandre Occidentale	0.017
	ES43	Extremadura	0.017
	ITF3	Campania	0.016

Table 4: The most and least diverse regions with respect to the continental shares of foreigners (%)

2001	NUTS 2 Codes	Regions	Diversity index	Share of foreigners	Afr	Ame	Asi	Eur	Rest	Total
most diverse regions	UKI1	Inner London	0.760	0.333	0.23	0.16	0.26	0.3	0.05	1
	UKM1	NE Scotland	0.732	0.045	0.12	0.17	0.25	0.4	0.06	1
	UKI2	Outer London	0.730	0.227	0.24	0.1	0.35	0.28	0.03	1
	UKJ1	Berkshire, Bucks and Oxfordshire	0.730	0.108	0.16	0.13	0.31	0.36	0.04	1
	UKH1	East Anglia	0.728	0.063	0.11	0.24	0.22	0.39	0.04	1
least diverse regions	AT12	Niederosterreich	0.093	0.088	0.01	0.01	0.02	0.95	0,00	1
	AT31	Oberosterreich	0.084	0.105	0.01	0.01	0.02	0.96	0,00	1
	AT21	Karnten	0.073	0.080	0.01	0.01	0.02	0.96	0,00	1
	AT33	Tirol	0.063	0.124	0.01	0.01	0.01	0.97	0,00	1
	AT34	Vorarlberg	0.057	0.154	0,00	0.01	0.01	0.97	0,00	1

Table 5: Random Effects Panel Models with Annual Data 1991-2001

VARIABLES	Dep. var.: ln $P_{i,t}$	Dep. var.: ln $P_{i,t}$	Dep. var.: ln $P_{i,t}$
	I	II	III
ln(share of foreigners)	0.232***	-	-
	(0.0863)		
african	-	2.616	-
		(7.718)	
americans	-	39.00***	-
		(13.16)	
asians	-	-24.17***	-
		(8.290)	
europeans	-	0.770	-
		(1.475)	
diversity index	-	-	2.243***
			(0.804)
services/industry value	-0.176***	-0.200***	-0.192***
	(0.0390)	(0.0403)	(0.0420)
ln(gdp)	1.031***	0.768***	0.989***
	(0.159)	(0.168)	(0.168)
ln(average population)	0.302***	0.199***	0.282***
	(0.0596)	(0.0665)	(0.0636)
accessibility index	-	0.0124***	-
		(0.00285)	
human resources	0.00740	0.00297	0.00570
	(0.00529)	(0.00551)	(0.00549)
constant	-3.933***	-3.366***	-4.396***
	-1.247	-1.211	-1.195
country dummies	Yes	Yes	Yes
time dummies	Yes	Yes	Yes
R^2 within	0.309	0.317	0.317
R^2 between	0.822	0.843	0.814
R^2 overall	0.744	0.762	0.738
Number of observations	1253	1201	1205
Number of cross-sections	169	162	163
Estimation technique	Random effects panel with AR(1) errors	Random effects panel with AR(1) errors	Random effects panel with AR(1) errors

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

Table 6: Panel models with period data (1991-1995 and 2001-2005)

Dep.var.: $\ln Pave_{i,t}$	(1)	(2)	(3)	(4)
ln(share of foreigners)	0.155**			0.244***
	(0.0550)			(0.061)
diversity index			1.546***	1.357***
			(0.409)	(0.403)
north-Africans		0.951		
		(0.0717)		
other-Africans		0.167**		
		(0.0824)		
Americans		0.191**		2.533**
		(0.095)		(1.169)
Central & Eastern Europe		0.363***		
		(0.100)		
other Europeans		0.277		
		(0.295)		
services/industry value	-0.0617	-0.216**	-0.229***	-0.236***
	(0.0681)	(0.0704)	(0.0633)	(0.068)
ln(gdp)	0.320	0.568**	0.372	0.281
	(0.217)	(0.271)	(0.294)	(0.253)
ln(average population)	-0.182	0.161**	0.113**	0.114**
	(0.793)	(0.0570)	(0.0523)	(0.0520)
human capital stock	-0.0203	0.0640***	0.0754***	0.0607***
	(0.0328)	(0.0119)	(0.0110)	(0.0116)
Time/Country dummy	Yes/No	Yes/Yes	Yes/Yes	Yes/Yes
Constant	5.685	-3.006**	-1.762	0.067
	(11.89)	(1.395)	(1.275)	(1.339)
N	297	297	297	297
R^2 overall	0.0932	(Adj) 0.889	(Adj) 0.895	(Adj) 0.909
R^2 within	0.773			
R^2 between	0.134			
Estimation technique	FE	OLS	OLS	OLS

Robust standard errors in parentheses *** <0.01, ** <0.05, * <0.1. The two Asian categories Middle East and East Asia) are not reported in Table 5 to save space. They are not statistically significant.

Table 7: Instrumental Variables Estimations

Dep.var.: $\ln Pave_{i,t}$	(1)	(2)
ln(share of foreigners)	0.496***	-
	(0.134)	
diversity index	-	0.592**
		(0.284)
services/industry value	0.123	-0.230***
	(0.102)	(0.0616)
ln(gdp)	-0.689	0.448
	(0.667)	(0.283)
ln(average population)	-0.0437	0.107**
	(0.829)	(0.0541)
human capital stock	-0.0218	0.0834***
	(0.0202)	(0.0130)
Time/Country dummy	Yes/No	Yes/Yes
Constant	9.257	-1.709
	(11.66)	(1.276)
N	297	297
R^2 overall	0.0231	(Adj) 0.889
R^2 within	0.626	
R^2 between	0.002	
Estimation Technique	2SLS, FE	OLS

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

Table 8: Estimations of Spatial Effects

Dep.var.: $\ln Pave_{i,t}$	(1)	(2)
ln(share of foreigners)	0.209***	-
	(0.0632)	
diversity index	-	1.375***
		(0.403)
services/industry value	-0.242***	-0.225***
	(0.0679)	(0.0618)
ln(gdp)	0.386	0.311
	(0.274)	(0.286)
ln(average population)	0.139**	0.163***
	(0.0555)	(0.0538)
human capital stock	0.0697***	0.0729***
	(0.0112)	(0.0112)
Time/Country dummy	Yes/Yes	Yes/Yes
Constant	-0.449	-1.830
	(1.500)	(1.289)
Lambda	0.726***	0.749***
	(0.178)	(0.168)
Observations	266	266
LR	-214.9	-215.2
LM	7.564	10.60

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.

Figure 1: Distribution of patent applications across NUTS 2 regions, 1991-2001

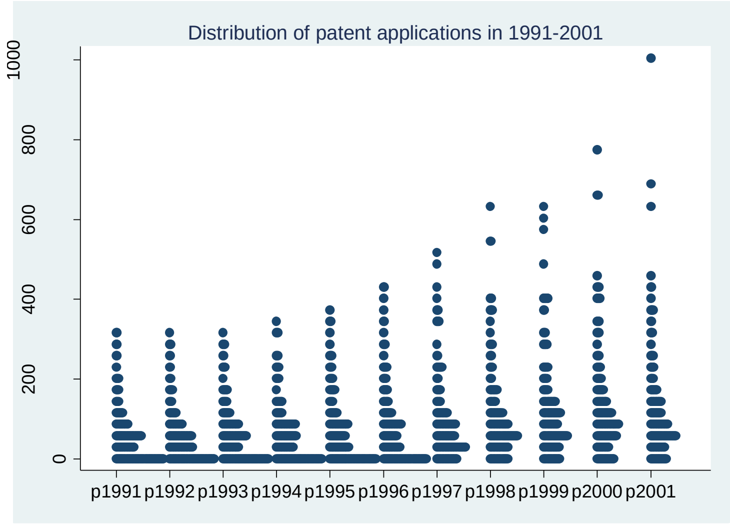
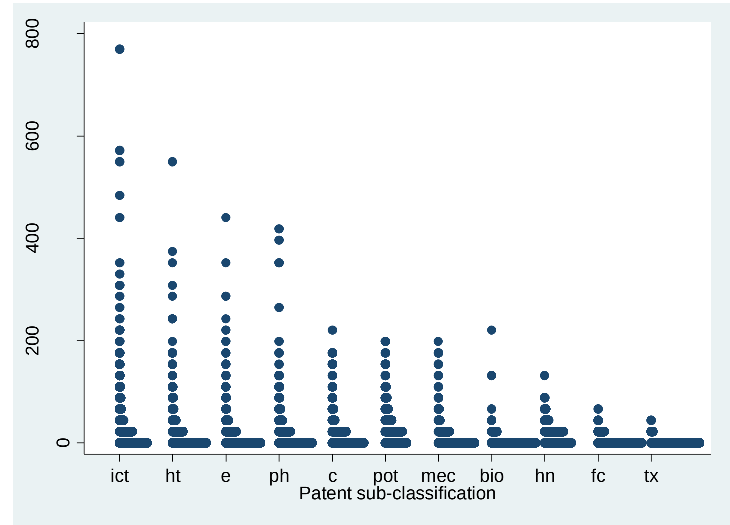


Figure 2: The distribution of patent applications across sub-categories, annual regional observations from 1991 until 2001 pooled



ht	High-tech
ict	ICT
bio	Biotech
e	Electricity
fc	Fixed constructions
ph	Physics
mec	Mechanical engineering
tx	Textiles and papers
hn	Human necessities
pot	Performing ope.; transporting
c	Chemicals

Figure 3: Distribution of the share of foreigners in Europe in 2001

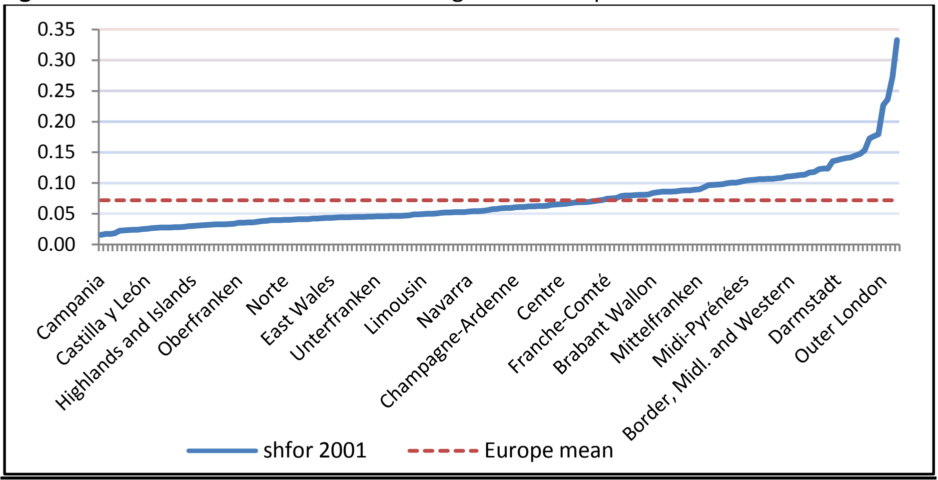


Figure 4: Scatter plot for patent applications per inhabitants vs share of foreigners in the regions in 1991 and 2001

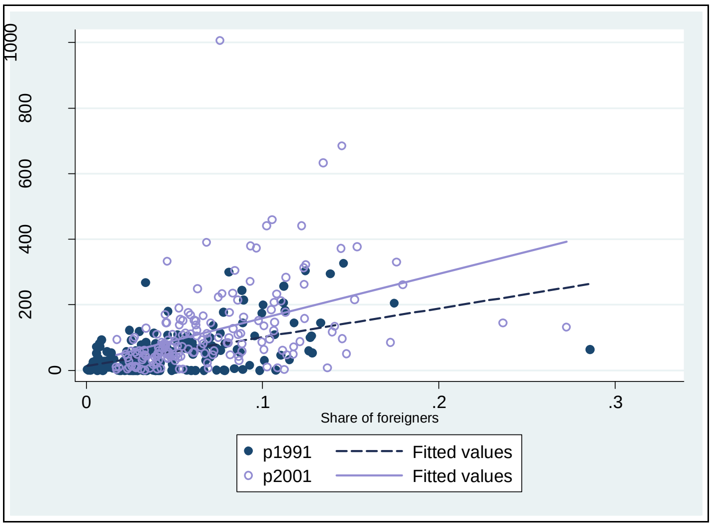


Figure 5: Patent Applications by Regions in 2001

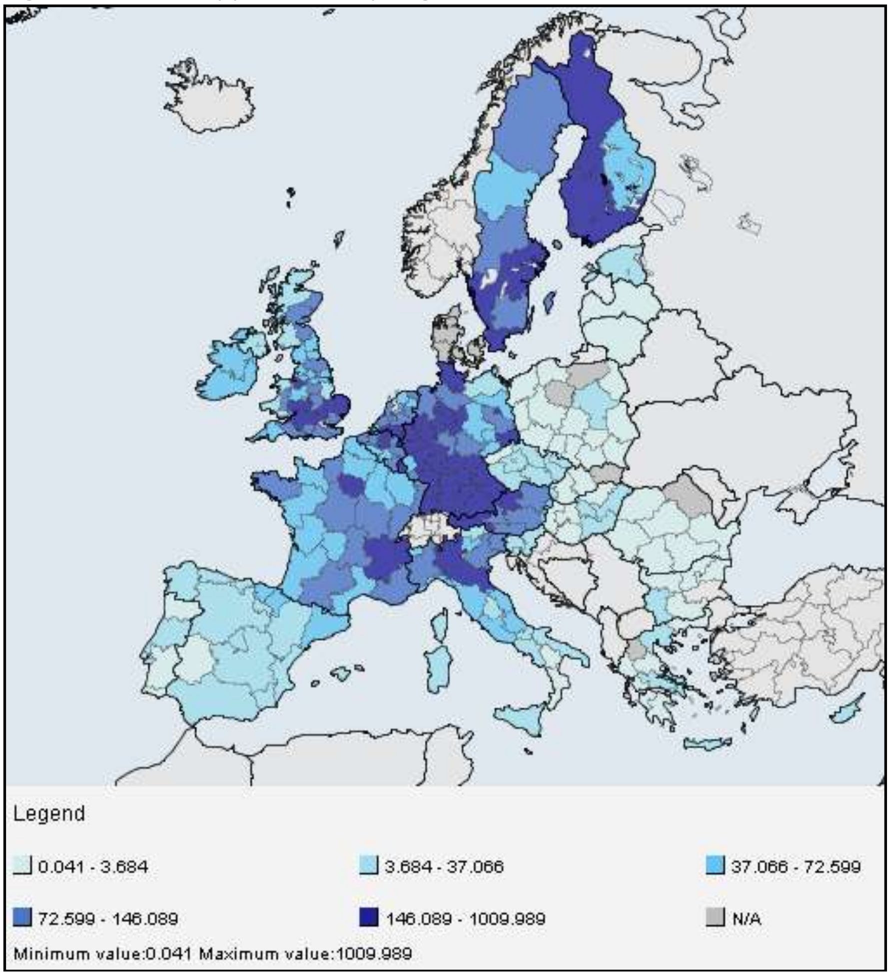


Figure 6: Estimated effect sizes for diversity index including natives

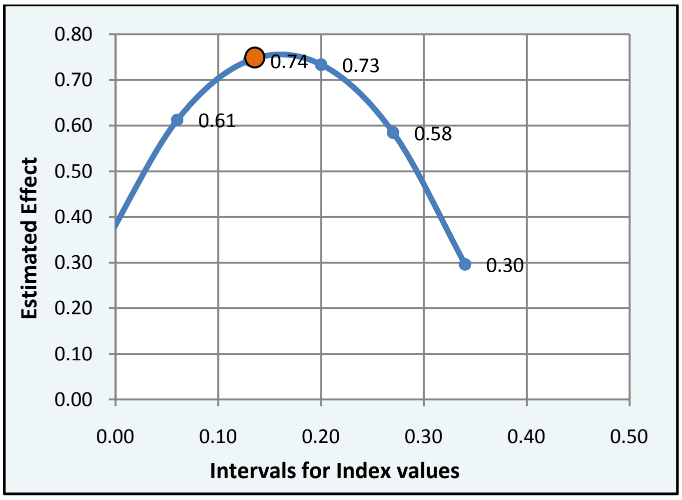


Figure 7: Estimated effect sizes for diversity index excluding natives