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Migration, Cultural Diversity and Innovation: A European Perspective

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Abstract

This paper analyses the effect of skilled migration on two measures of innovation, patenting and citations of scientific publications, in a panel of 20 European countries. Skilled migrants positively contribute to the knowledge formation in host countries as they add to the pool of skills in destination markets. Moreover, they positively affect natives' productivity, as new ideas are likely to arise through the interaction of diverse cultures and diverse approaches in problem solving. The empirical findings we present support this prediction. Greater diversity in the skilled professions are associated with higher levels of knowledge creation, measured either by the number of patents applied for through the Patent Cooperation Treaty or by the number of citations to published articles. This finding is robust to the use of different proxies for both the explanatory variables and the diversity index in the labour force. Specifically, we first measure diversity with a novel indicator which uses information on the skill level of foreigners' occupations. We then check our results by following the general literature, which measures skills by looking at the foreigners' level of education. We show that cultural diversity consistently increases the innovation performance of European Countries.

Keywords: cultural diversity, innovation, skilled migration, knowledge production function, Europe

JEL: F22, J24, O31

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1. Introduction

Endogenous growth theory highlights that knowledge and technology formation, along with the way in which they are modelled, have important repercussions for productivity and growth (Solow 1957; Romer 1990; Aghion and Howitt 1992; Grossman and Helpman 1994; Jones 2009). The vast literature on the determinants of innovative activity, motivated by Hicks (1932), Schumpeter (1942) and Schmookler (1966) and recently reviewed by Cohen (2010), focuses on the role of firm size (Cohen and Klepper 1996), market structure and industry dynamics (Geroski 1991), market concentration (Arrow 1962), technological opportunity (Jaffe 1986) and national innovative capacity (Furman et al.2002).

A core contributor to the knowledge production function is specialized labour force, namely high-skilled workers engaged in research or academia (Caballaro and Jaffe 1993 and Kerr and Kerr 2011). Labour force characteristics which impact the level of innovation in a given country are not limited to the level of education and the number of workers engaged in research, but include measures of cultural and ethnic diversity of the workforce (Kerr 2008, Stuen et al., 2012).

This paper marries the literature on innovation and knowledge production function with the literature on diversity, migration and productivity. The issue of foreign skilled labour and its contribution to innovation is relatively understudied in Europe, but it is relevant because EU countries, once "source" of migration, are increasingly seen as migration destinations for skilled and unskilled foreign workers.[1] In 2007 third-country high-skilled workers represented 1.7 percent of the total European workforce (EC 2007). Indeed, attention has been increasingly drawn to the role of high skilled immigration and cultural diversity as a driver of technology development, innovation and economic performance (EMN 2006; EC, 2007; EC, 2008).

This debate traces back to the Lisbon European Council in March 2000 which set the objective for Europe to become the most competitive and dynamic knowledge-based economy. In October 2007, the European Commission adopted two proposals in line with this objective: The first established a Framework Directive on the admission of highly educated migrants to the EU and the second aimed at simplifying migration procedures. In May 2009, the European Council adopted the EU Blue Card directive and the single permit directive was adopted in December 2011. In early 2012, Germany and Italy, among the last countries who had not yet ratified the European directive, also approved the Blue Card scheme. A major concern will now become the assessment of the overall effects of the Blue Card Scheme and its effectiveness in attracting high skilled labour into the EU borders (Euobserver 2009, EC 2009, EC 2011).

[1] In 2008, third countries migrants to the EU represent around 3.8 percent of the total population according to EU Commission. Between 1.5 and 2 million migrants per year have entered the EU since 2002. As of January 2006, 18.5 million third-country nationals were resident in EU member countries (EC 2008).

Notwithstanding the lively political debate, empirical evidence on the contribution of skilled foreigners to knowledge creation in European countries is scarce.[2] The main contribution of the present paper is to fill in this gap by providing novel evidence on the effect of skilled foreigners on innovation and knowledge production in a panel of 20 European countries. Most of the literature in this respect focuses on the USA (Stephan and Levin, 2001; Peri, 2007; Chellaraj at al., 2008; Kerr, 2008; Hunt and Gauthier-Loiselle, 2010; Kerr and Lincoln, 2010; Stuen et al 2012; Peri, 2012). Only few analyses are focused on selected European countries. Niebhur (2010) and Ozgen et al. (2011) test the hypothesis that the ethnic diversity of skilled labour has a positive effect on innovation (as measured by patents) in German regions and selected Western European regions, respectively.[3]

The second novelty of our analysis is the use of two different proxies of innovative performance. We use patent data to explore the contribution of skilled workforce diversity to the production of products or processes that can be generally diffused in the market and are superior to the previously available alternatives. In line with the embedded technological change hypothesis, the number of blueprints (patents) available in a given market has a direct impact on the "quality" of products and/or the efficiency of production processes. Conversely, we use proxies of academic endeavours, namely publication statistics, to look at the impact of diversity on more intangible knowledge. The latter represents more closely basic scientific research performance, which possibly has a less direct application to the market but nonetheless is fundamental to ensure the fostering of science and technological change. Both variables have been used in the empirical literature as a proxy for innovation but, to our knowledge, none of the papers use them simultaneously.

Third, we use two different indexes to measure cultural diversity of the skilled labour force. First, we propose a novel indicator which uses information on the skill level of foreigners based on their actual occupation. We then check our results by following the general literature, which commonly measures skills by looking at foreigners' level of education.

One of the main concerns when estimating the effect of diversity on innovation indicators is the endogeneity of migration flows. To address this issue appropriately, we draw heavily from contributions on the static effect of migration. These studies are concerned with the effect of migrants on native employment and wages (Alesina and La Ferrara 2005; Ottaviano and Peri 2012) as well as on the issue of skill-complementarity and task specialization (Peri and Sparber 2009).

The paper is organized as follows: Section 1 reviews the relevant literature and highlights the contribution of the present work. Section 2 presents a model of knowledge production function which

[2] Within the European context, papers have mostly concentrated on labour market impact of migrants (D'Amuri et al., 2010), their role in fostering trade relations (Iranzo and Peri 2009), the emigration of high-skilled natives (Saint-Paul 2004), preferential destinations (Constant and D'Agosto 2008) and on the potentials of re-migration (Mayr and Peri, 2009).

[3] The analysis of Ozgen et al. (2011) is based NUTS2 regions in 12 EU countries: Austria, Belgium, Denmark, France, Western Germany, Ireland, Italy, Netherlands, Portugal, Spain, Sweden and the UK.

highlights the role of diversity. Section 3 presents the empirical specification and the data we select. Section 4 and 5 present the empirical results and sensitivity analysis, respectively. Section 6 concludes.

2. Literature Review

The literature addressing the role of technological process and innovation in the growth process is vast. Cardinal to the models of R&D-based endogenous growth is the knowledge production function, which is typically a function of labour force in the research sector and of the available stock of knowledge (Romer 1990; Aghion and Howitt 1992; Grossman and Helpman 1994). This knowledge stock records the history of discoveries and ideas and allows researchers to stand "on the shoulder of the giants" (Caballero and Jaffe 1993). Many are the contributions pointing out that both the way in which the production of knowledge is specified and its functional form have important implications for theoretical predictions. Also, theoretical models should be tested with available empirical data (Jones 2009; Abdih and Joutz 2006).

There is a vast empirical literature on the determinants of innovation. Both micro and macro analysis focus on issues of inter-temporal, inter-sectoral and international spillovers (Jaffe 1986; Coe and Helpman 1995; Malerba 1992; Mancusi 2008; Branstetter 2001) and explore the role of policy, property rights and market structure in fostering further innovation (Cohen and Klepper, 1996; Geroski 1991).

A second strand of empirical research focuses on the characteristics of the research labour force as input to the innovation production function. In this respect, the composition of the pool of researchers is a key element. In the evolution of scientific activity, the leading role of any research endeavour is increasingly played by the research team rather than the individual researcher. The paradigm of solo geniuses has slowly been replaced by that of large networks, bridging diverse knowledge, linking different problems and perspectives (see for example Hargadon 2003 and Barabási 2005). Diversity in the research team is seen as beneficial partly because it is believed that problems and technical bottlenecks are characterized by an increasing level of complexity. The ability to tackle such problems and overcome them thus exceeds the capacity of a single brain (Jones, 2009). Diversity might refer to differences in background knowledge and abilities, age, gender, but also to differences in the nationality and culture of team components. If the positive effect on productivity exerted by differences in ability and knowledge is uncontroversial, see for example (Hamilton et al., 2003 and Lazear, 2009), the effect of cultural diversity is ambiguous. Indeed cultural diversity imposes communication costs that might offset the creative benefits induced by complementarity (Bassett-Jones, 2005, Stahl et al., 2009). However, the results of studies looking at micro data point to a prevailing beneficial role of cultural diversity. In (Parrotta et al., 2010), the propensity to patent of a population of Danish firm is found positively influenced not only by skill diversity but also by cultural diversity of the work force. (Younglove-Webb et al.1999, Katz and Martin 1997) look into academic innovation ability and emphasize the importance of a diverse team and of international collaborations. An

investigation into the Rockefeller Institute's scientific success stresses the positive contribution of foreign permanent staff as well as that of visiting scientists (Hollingsworth & Hollingsworth, 2000). .

Building on these micro-founded concepts, the macro literature looks at immigration and cultural diversity as a preferential channel for knowledge and productivity spillovers. The existing contributions are mainly focused on the USA and look at the dynamic effect of migration and at the effect of (high skilled) foreigners and cultural diversity on the innovative capacity of US firms and universities. Results generally suggest that foreign skilled workers and higher diversity in research personnel are associated with higher levels of innovative activity and patenting. For example, Chellaraj et al. (2008) and Peri (2007) highlight the positive contribution of highly educated foreign-born workers and foreign graduate students to US patenting activities. Hunt and Gauthier-Loiselle (2010) show that overrepresentation of immigrant graduates in science and technology disciplines leads to double a patenting rate with respect to natives. Kerr and Lincoln (2010) find that larger immigration waves increase overall patenting activity with no crowding out effect on natives. The role of ethnic scientific communities in promoting technological transfer is investigated in Kerr (2008), while Kerr (2010) argues that the positive impact of immigration can be explained by higher mobility of foreign skilled labour force which can more easily relocate and cluster around the loci of a breakthrough. Stuen et al. (2012) analyse the contribution of foreign born students to faculty publications and citations. Stephan and Levin (2001) report that foreign-born and foreign-educated workers disproportionately provide exceptional contributions to science and engineering, through a list of indicators such as election to the National Academy of Sciences and/or National Academy of Engineering, authors of citation classics, authors of hot papers, the 250 most-cited authors, authors of highly cited patents, and scientists who have played a key role in launching biotechnology firms.

All this literature focuses on the USA, where immigrants represent a significant share of highly educated workers.[4] On the contrary, the impact of cultural diversity on innovation in Europe is under-researched. To our knowledge, only two contributions can be quoted. Niebhur (2010) and Ozgen et al. (2011) are the unique tests on the effect of ethnic diversity of skilled labour on EU innovation (as measured by patents). In both works cultural diversity is found to have a positive effect on patenting activities.

3. Methodology

We propose a simple model describing the innovation production function, in line with the R&D-based models presented in Romer (1990) and Grossman and Helpman (1991). In this set up, the stock of knowledge for country, A , represents the accumulation of all ideas and blueprints available at period t in

[4] In the USA, 3.2 percent of the labour force is high skilled foreign workers (EC 2007). According 2000 Census data, for example, 24 percent and 47 percent of the US science and engineering (SE) workforce with bachelors and doctorate educations are immigrants. The corresponding statistics for the general working population in the USA is 12 percent.

that country. The creation of new ideas, $\dot{A}$, depends on the number of people employed in the research sector L_i^A, and the average productivity per researcher, $\bar{\delta}$.

$$\dot{A} = \bar{\delta}\, L_A \tag{1}$$

We assume that average productivity per researcher is a function of three key factors. The first is the capital of knowledge, cumulated in a country and which allows current researchers to "stand on the shoulders of giants" (Stern et al. 2000). The second factor is the number of researchers, L_A, to capture the potential decreasing of returns as the number of researcher in a country increase, the so called "stepping on toes" effect. The third factor, which is the core interest of this paper, is an indicator of cultural diversity of the skilled labour forces employed in the research sector, $\mathrm{D}_{\mathrm{L_A}}$. Hence $\bar{\delta}$ can be defined as :

$$\bar{\delta} = (A)^{\alpha}\,(D_{L_A})^{\beta}\,(L_A)^{\vartheta-1} \tag{2}$$

and equation (1) becomes:

$$\dot{A} = (A)^{\alpha}\,(D_{L_A})^{\beta}\,(L_A)^{\vartheta} \tag{3}$$

Equation (3) is the basis of our estimation in this paper. Our interest lies in the estimation of β, which informs on the impact of diversity on knowledge production, by controlling for other confounding factors.

Finding a good proxy for knowledge and its dynamics, $\dot{A}$, has been the matter of much debate in the literature. A commonly used statistics is patent applications. Patents are legal titles protecting a product or a process, which are granted to the patent assignee by a given patenting authority.[5] Different application "routes" result in different patent rights. Specifically, a patent applicant can chose to apply for a patents at a specific national office, effectively gaining patent rights in one single "market", or to apply for patent rights at a "regional" office or through the Patent Cooperation Treaty, thus eventually obtaining patent rights in more than one country.[6] The use of patent statistics as indicators of innovative activity has been validated by a number of micro and macro studies. [7] Patents are linked with the output of the R&D process, and inform on the number of technological blueprints available in any given market.[8]

[5] To be eligible for a patent, an invention (device, process, etc.) needs to be new, susceptible of industrial application and to involve a non-obvious inventive step. To obtain a patent, an inventor has to file an application to a patenting authority. The patenting office will check whether the application fulfils the relevant legal criteria and will grant or reject the patent accordingly. The patent ensures the owner the right to assign, or transfer by succession, the patent and to conclude licensing contracts.

[6] These "routes" are generally referred to as the national route, the regional route or the international route. In the national route, the inventor files an application with a national patent office (generally, but not always, the national office of the applicant's country). Alternatively, applicants can use the PCT (Patent Cooperation Treaty) procedure, which has been in force since 1978 and is administered by the World Intellectual Property Organization (WIPO). The PCT allows applicants to apply for patent rights in more than one jurisdiction. This is a very popular route among inventors targeting worldwide markets. One last option for applicants is to submit a patent application to a regional office, such as the European Patent Office (EPO), established in 1977, which searches and examines patent applications on behalf of 38 member countries. The EPO grants "European patents", which are valid in all the member states where the holder has validated her rights.

[7] The use of patents as an imperfect indicator of inventive activity is validated in a number of studies (Pakes and Griliches 1984; Griliches, Pakes, and Hall 1987; Pavitt and Soete 1980; Sokoloff and Khan 1990). In this extensive

Patents statistics present some clear limitations (Griliches, 1990).[9] The most important in our case is that they do not capture the inventions which are not patented or patentable, or more in general might not be the best indicator of general knowledge in society. We thus provide an alternative measure of knowledge production in a given country by counting the number article citations received yearly by researchers in each country. Whereas patents are indicative of innovations with some practical application (at least on average), publications are much more related to basic research and knowledge. The use of two proxies allows not only allow to check the robustness of our finding, but also to disentangle differences, if any, in the effect of our variable of interest (diversity) on innovations of inherently different nature.

In our analysis we want to focus on high impact innovation. As far as patents are concerned, we count the number of patents filed under the PCT by applicants of each country at time t. Patents statistics are counted by priority date. This ensures that each patent application is attributed to the year closer to the actual invention (OECD 2009). Using PCT application to proxy for innovative activity is a way to provide a "quality threshold" and to weed out from our sample patents of "lower" quality or used for strategic patenting. PCT applications are more costly than applications to national offices, and they represent those innovations that the inventor would like to exploit in more than one market. As such, they represent higher quality innovations and are a much cleaner proxy than number of applications at each national or regional patent office.[10]

Regarding documents, we use a country aggregate of citations. This is a widely used indicator of the impact of a university's (Stuen et al, 2012) or a nation's research output (King, 2004). We use it under the assumption that publications which are more cited are those of higher quality. Cited publications contain ideas that have been subsequently useful to other researches. Focusing on citations is tantamount to weighting each country's publications by a measure of quality.

Patent data are obtained via the OECD Patent Statistics Database (OECD, 2011), while data on citations comes from the SCImago Journal & Country Rank (SCImago, 2011). The correlation between PCT Patent

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literature patent data has been used to study the dynamics of both innovation and inter-sectoral and international knowledge flow and spillovers at the firm, sector and country level (Jaffe 1986, Jaffe and Trajtenberg 1996, Peri 2005, Globerman, Kokko, and Sjöholm 2000 among others).

[8] Patents are an imperfect indicator of innovative activity. Griliches (1990) summarizes the limitations in using patents as a proxy for innovation: (1) not all innovations are patented, thus patent data is only a partial indicator of innovative activity, (2) not all patented innovation have the same level of quality, meaning that simple patent counts do not account for this difference, (3) related to point (1) above, propensity to patent changes across countries, sectors and time, so that researchers need to be careful when comparing data for different countries and sectors and (4) the number of patent granted is inextricably linked with budget constraints of the patenting offices. In addition, patent data can shed light only on the dynamics of embodied technological change, namely those innovations that are embedded in new machinery. Conversely, patents do not provide any insight on disembodied technological change, such as the "learning-by-doing" which also increases productivity. Such issues are clearly left out of a study based on patent data.

[9] See Footnote 8

[10] The NBER Patent Database on USPTO Patents is an exception in this respect, but it is not the best source of data for our study, since it provides information patents granted in the USA market, which would not be the core focus of innovation for European applicants.

application and citations is reasonably high, namely 0.74. This indicates that countries that are highly productive in the production of patentable knowledge do well also in terms of general knowledge (Figure 1).

Our explanatory variable of interest is cultural diversity in the high skilled portion of the labour force, D_{L_A}. The empirical literature proxies cultural diversity with ethnic diversity and computes the share of foreigners in the total population. Given that we study the process of innovation, we consider only skilled foreigners and therefore we compute D_{L_A} as the number of foreigners employed in top skill occupations over total employed in top skill occupations.[11] To identify top-skill occupations we use the Standard Classification of Occupations (ISCO-88) by the International Labour Office (ILO, 1990). This standard classification takes into consideration the kind of work performed as well as the skill embodied in the work (Elias and McKnight, 2001). According to ISCO-88, occupations can be grouped together according to the similarity of the skills involved in the fulfilment of the tasks and duties of the jobs. In particular, "skill is defined as the ability to carry out the tasks and duties of a job in a competent manner" (ILO, 1990). Within ISCO-88, four skill levels are defined. Broadly, the different levels mirror the length of time a person requires to become fully competent in the performance of the tasks associated with her job. For a description of the complete classification into the four skill groups, see Table 1.

In this paper, only foreigners occupied in the third and fourth skill groups are considered. The third skill level applies to occupations that require post-compulsory education. Technical occupations belong to this category. The fourth skill level requires a degree or equivalent period of relevant work experience and typically relates to professional occupations and managerial positions in corporate enterprises or national/local government such as legislators, senior officials and managers. In the EU27, the third and fourth skill group accounts for 16.5 and 22.2 per cent of total employed, respectively (Table 2).

The composition mix of the foreign labour force by skill group varies among the different European countries (Figure 2). In the UK, Ireland, Hungary, Romania and Poland, the share of skilled foreigners in skilled labour is more than proportional to the overall foreigner share. Except for Finland, the Slovakia and the Czech Republic, where the two shares are almost similar, all other European countries display a skilled share lower than the overall share, with some cases where the two shares are remarkably different (Austria, Germany and Greece).

The skill dimension embodied in our measure of diversity is not standard. Conventionally, the empirical literature considers the educational attainment of the foreign labour force independently from occupation considerations (among others, Borjas, 2003; Card and Shleifer, 2009; Ottaviano and Peri, 2012). Here, on the contrary, we focus on the occupation that the foreigners actually perform. This captures the actual contribution of the foreign labour force to the creation of new knowledge. This distinction should matter

[11] Other more sophisticated measures of diversity used in the literature include the Herfindhal index. The availability of data for this study prevents us from constructing such an index.

more for foreigners than for natives, as in the literature it is found that skill mismatch is more likely to occur among migrants (Green et al., 2007).

In addition, the skill classification described above takes into consideration the content of the educational capital embodied in different occupations. The formal education required to fulfil tasks and duties associated with a given occupation is one of the dimensions considered for the ISCO-88 aggregation (ILO, 1990). As a robustness check, however, we also show results employing cultural diversity within the skilled population, where skills are defined on the basis of educational attainments.

The data to compute the share of foreigners in the third and fourth skill levels is taken from the EU Labour Force Survey (EU-LFS), which provides, consistently among all European countries, information on nationality of the respondents as well as details of the occupation performed, classified according to ISCO-88.[12] The EU-LFS has the great advantage to produce highly comparable data for the EU member states, as a common coding of questions, definitions and classifications of the variables is used. A caveat of this dataset is that it does not cover illegal migration. This limitation however should not be problematic in this context. The component of diversity that affects innovation is provided by highly skilled foreigners, who are most likely employed legally in high skilled occupations. Highly qualified foreigners entering illegally European countries eventually find low-skilled jobs and do not influence the innovation potential of a country.

A second limitation of the data is that at the beginning of the sample years foreigners were classified only as national or non-nationals. From 2004 onwards migrants were classified by main area of origin, while detailed bilateral country information are never available. Therefore it is impossible to compute more sophisticated index, such as the Herfindahl Index, to measure ethnic diversity as the use of this index would restrict drastically the sample size as it is available only for four years. We believe, however, that this is a minor limitation. Given that the share of nationals enters the Herfindahl Index, and given that in European countries foreigners still account for a limited portion of total population, a diversity measure computed as the ration of foreigners over population and the Herfindahl index are highly correlated.[13] As a robustness check, we compute the Herfindahl index drawing from an alternative dataset, the OECD International Migration database, which is available from 1990 and provides bilateral stocks of migration. The limitation of this database is that it does not provide skill or education breakdown of foreigners. This implies that the Herfindahl index computed refers to the total migration population and not to the skilled one. Given that we study the innovation process, the index computed for the total foreign population does not represent our preferred measure of diversity.

[12] For most of the countries, the EU-LFS provides information on both the nationality and the country of birth of non-nationals. We decided to classify foreigners by nationality only as this was the most comprehensive information. The sample from Germany, for example, does not provide details on country of birth and some Eastern European countries, such as the Slovak Republic, the Czech Republic and Bulgaria, add information on country of birth only for a very limited number of years.

[13] The Herfindahl index, computed after 2004, and the ration of foreigners over population display a correlation of 0.99.

Equation 2 also requires a proxy for the labour force working in the knowledge sector, L_A, including foreigners and natives. An excellent candidate is the number of employees in technology and knowledge intensive sectors, which we obtain from the EUROSTAT database (EUROSTAT 2011). This variable serves for two distinct purposes. Given that we measure innovation by the total number of patents and citations and not by the per capita measures, a scale factor should be added into the estimated specification. The number of R&D workers, while representing one of the most important inputs in the knowledge production function, it does also capture the size of the countries.

To proxy for the "standing of the shoulder of the giants'" effect we follow the rich literature on the supply determinants of innovation and construct variables proxying for the knowledge stock of each country. We use data on yearly intramural R&D expenditure in any given country obtained from EUROSTAT database. We build a stock variable using the perpetual inventory method as the discounted sum of innovation at time t and the stock of the previous period t-1 following the formula:

$$A_t = R\&D_t + (1-\delta)A_{t-1} \qquad (4)$$

The initial value of the stock is calculated as follows:

$$A_{t_0} = \frac{P_{t_0}}{\bar{g}+\delta}$$

where δ=0.1 is the depreciation rate set chosen in line with the literature (Keller 2002) and $\bar{g}$ is the average rate of growth of patenting for the period between t_0 and $t_0 = 3$, where t_0 is the first year of data availability (Bottazzi and Peri 2003). As long as t_0 is chosen to be outside the sample period the stock measure is highly insensitive to choices of the discount rate used in the calculation reported in (4).

4. Discussion of Results

The model presented in section 3 is estimated on a panel of 20 European countries from 1995 to 2008. [14] Both the sample of countries and the time spell are constrained by the availability of data from the EU-LFS. The data forms an unbalanced panel, as for some countries the information are only available on a shorter time interval.

Taking the natural logarithm of equation (2) and explicitly introducing the time dimension, the basic specification, for each country *i* at time *t* becomes:

$$\ln(\dot{A}_t) = \beta_0 + \beta_1 \ln(A_{t-1}) + \beta_2 \ln(D_{L_A,t-1}\ ) + \beta_3 \ln(L_{A,t-1}) + \mu_t + \mu_i + \varepsilon_{i,t} \qquad (5)$$

The dependent variable $\dot{A}$ is, alternatively, the number of patent applications filed under the PCT recorded by priority date, and the number of citations; D_{L_A} the cultural diversity variable, computed as the

[14]The sample includes: Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Netherlands, Norway, Poland, Portugal, Slovak Republic, Spain, Sweden and the United Kingdom.

number of foreigners employed in top skill occupations over total employed in top skill occupations; L_A is the stock of skilled labour, measured by the number of employees in high-technology sectors; A is the knowledge stock described in equation (4); all are measured as end-of-period; μ_t is a set of year dummies; μ_i represents a set of country fixed effects and finally $\varepsilon_{i,t}$ is an idiosyncratic error term. [15]

We use lagged values of the independent variables to account for the fact that there is a time lag between the process of innovation and knowledge production and the application of a patent or the citation of a given article. One year time lag is used in the main analysis. This approach is in line with the literature that analyses the determinants of both patenting and citations. In the sensitivity analyses in Section 5 we also present results using higher lags to account for the length of the innovation process.

The specification described above assumes zero correlation between the error term and the exogenous variables. This assumption for the diversity variable is likely to be violated in this context. Some unobservables governing the location of foreigners in the different European countries might be correlated with the unobservables governing the evolution of patents or published documents. If migrants elastically respond to economic opportunities in destination countries, a non-zero correlation exists between the economic outcomes and the share of immigrants, biasing up-ward the estimated coefficient of the share of migrants. A second source of bias can derive from measurement errors in the share of foreigners, which, on the contrary, should produce a down-ward bias. For example, as pointed by Aydemir and Borjas (2011), the sampling error in the measures of immigrant supply shift is responsible for a substantial reduction in the estimated impact of migration on wages. This attenuation bias should therefore play a role in this context, counteracting the effect of the endogeneity bias. Which of the two prevails is only an empirical fact.

To address both biases, an instrumental variable approach is used. Antonji and Card (1991) suggest an "ethnic enclave" instrument that has been largely used in the subsequent empirical literature for migration shares (Card, 2001; Card and DiNardo 2000; Peri and Sparber 2009, Ottaviano, Peri and Wright 2010; D'Amuri and Peri 2011; Ottaviano and Peri, 2012). The instrument is an imputed share of migrants, which nets out the component of migration flows that are attributed to economic opportunities. We use past migration stocks, available with education breakdown in a bilateral form, to compute the instrument (Docquier et al., 2009). We select the 1991 stock of highly educated migrants and predicted the subsequent stock of skilled migrants using total yearly immigration flows by country of origin from Ortega and Peri (2011).[16] In agreement with D'Amuri and Peri (2011) we assume 40 percent re-emigration rate to net the total gross inflows available. Aggregating the data across area of origin, we calculate the shares as the ratio

[15] The OECD provides patent statistics which are calculated applying fractional counting. The use of count data models, which is common in the literature, is therefore not applied since our dependent variable is not a positive integer. Focusing on 20 (developed) European countries we also never observe 0 patents during our sample. Taking logs on both sides of equation (2) does not result in a loss of observations.

[16] While the 1991 stocks consider only the highly educated migrants, the inflows refer to the total number of foreigners entering the countries. The use of the overall flows should ensure that the instrument is independent to the error process, given that what drives the overall inflows are the ethnic ties rather than the economic shocks, which may be correlated with the skill composition of the inflows.

of the imputed stock of migrants and the total population, as it was in 1991. This methodology has the advantage that only the initial migration mix by origin and the variation in flows across origin groups in the different European countries determine the imputed shares. Given the importance of ethnic networks, migrants tend to locate where communities of similar origin are settled. Family reunification and ethnic ties are, therefore, the main drivers of country patterns of immigration flows by origin, rather than labour demand conditions. The underlying exclusion restriction for this instrument is that the 1991 settlement of migrants by origin is not correlated to the economic situation after 1996.

The primary sources of the 1991 migration stocks are Censuses and Registers. These sources provide highly reliable information on the structure of immigration in all OECD countries. These data should be less affected by sampling errors than survey data and for this reason they adequately address the measurement error bias.

We now turn to the discussion of the results. Table 3 reports the estimates of the OLS and 2SLS regressions, for the two measures of innovation. The diversity variable, proxied by the share of skilled migrants, exerts a clear effect on both measures of innovation. The coefficient of diversity is positive and statistically different from zero in all specifications. A one percent increase in the share of skilled migrants increases the number of patents by 0.1 percent in OLS and 0.3 percent in 2SLS, on average and *ceteribus paribus*. Comparable elasticities are found in the citation specification.[17]

The elasticities in the 2SLS increase considerably compared to the OLS estimates. As mentioned we perform our analysis using a 2SLS procedure to correct for two possibly confounding effects: the presence of on unobservable affecting both the dependant variable and our cultural diversity measure and the potential noise affecting our diversity variable. The former effect would see a decrease in the estimated elasticity once the signal is cleaned through the instrumental variable approach. The increase in the elasticity value tells us that the second effect is indeed prevailing.[18]

Regarding the coefficients of the standard controls for innovation, they are all in line with expectations. The variable measuring the stock of knowledge in a given country (stock of R&D expenditure) exerts a positive and statistically significant effect on innovation. A 1 percent increase in the stock of R&D expenditures is associated with a 0.6 percent and a 0.4 percent increase in patent application and citations,

[17] Diversity may positively contribute to knowledge creation but only up to a certain level of diversity. Too large diversity may entail costs from potential conflicts of preferences and hurdles of communication. To test a non-linear impact of diversity on innovation, a squared term has been introduced. The coefficient resulted not statistical significant. This finding may indicate that the level of diversity in Europe is still too limited to detect an inverted-U shape relationship.

[18] We largely emphasized in the text the importance of diversity within the highly skilled portion of the labour force. However, the instrument selected may capture the diversity of the overall labour force, which comprises skilled and un-skilled workers. We are not able, however, to detect if this is the case. If we replace the overall share of foreigners in the first stage estimation, the instrument proves to be quit powerful, with an estimated coefficient comparable to the one reported in Table A1. It should be noted, that the share of skilled foreigners and the share of overall foreigners are highly positively correlated in the sample of countries. This implies that the main conclusion of this analysis may be that ethnic diversity and not necessarily ethnic diversity of the highly skilled has a positive effect on innovation.

respectively. The elasticity is larger in the patent compared to the citation specification. The positive coefficients drive in favour of the "standing on shoulders" assumption, as far as the accumulation of past knowledge increases, it benefits the creation of new knowledge. This is consistent with the R&D-based growth models of Romer (1990) and Jones (1995). The coefficient is statistically smaller than one, indicating a weaker degree of intertemporal spillovers than that found in Abdih and Joutz (2006).

Finally, as expected, a larger pool of skilled labour increases the productivity of knowledge. Sometimes the coefficient is not statistically significant, although it is always significantly greater than zero in the 2SLS specifications. As before, we find a larger elasticity if innovation is measured by patentable knowledge rather than by citations. The coefficients of the skilled labour is statistically smaller than one, indicating decreasing returns to scale. The productivity of the skilled labour force decreases as the number of people searching for ideas increases, as it is more likely that efforts are duplicated and overlapping. Our estimate, ranging between 0.2 and 0.4, is in line with what found in Abdih and Joutz (2006) and within the range in Kortum (1993).

The first stage estimates for the excluded instrument are reported in the Appendix, Table A1. In line with the existing empirical literature, the imputed shares of highly educated migrants exert a positive and well defined effect on the actual share of skilled migrants. The F-test is 22, indicating that the instrument is fairly powerful. The statistic is greater than the value suggested by Staiger and Stock (1997) as a rule of thumb to assess the relevance of the instruments.

In line with what is found for the US (Stephan and Levin, 2001; Chellaraj at al. 2008; Kerr 2008, Hunt and Gauthier-Loiselle, 2010; Kerr and Lincoln, 2010; Stuen et al 2012; Peri, 2012) and the few studies considering a sub set of European countries (Niebuhr 2010 and Ozgen and al 2011), we find that cultural diversity plays a role not only through the direct channel of increasing skilled labour, but also by an indirect effect on skilled labour productivity. Foreigners positively affect natives' productivity, as new ideas are likely to arise through the interaction of diverse cultures and diverse approaches in problem solving. Not only high skill immigrants display high rates of patenting, but they also allow natives to produce greater innovation. This conclusion is also supported by Hunt and Gauthier-Loiselle (2010) as well as Kerr and Lincoln (2010).

We are aware that "the type of diversity" matters for economic development. First, not only the share of overall foreigners but also the variety of ethnicity available, namely the country mix, is relevant. Second, some ethnicities, given the language spoken, my better interact with nationals than others, thus providing larger complementarities. AS already discussed however, the available EU-LFS does not allow to capture such details as foreigners are only classified as non-nationals. The International Migration database on the contrary provides detailed bilateral information of origin and destination countries. The limitation of this dataset is that it does not offer a skill breakdown of movers. The distribution of skilled foreigners by origin country in the different destinations may not be proportional to the distribution of total foreigners. Skilled

and unskilled foreigners may follow different channels of entry, with the former being more likely to exploit family ties.

Despite this limitation, we compute the Herfindahl index, to capture the variety and the distribution of the nationalities of foreigners, keeping in mind that the limitation described may reduce the reliability of the index. Given that we control for the size of the (skilled) foreign population by adding the share of migrants, we exclude natives from the Herfindahl index. The two variables capture distinct factors: the share captures the density of migrants, while the Herfindahl captures the diversity of migrants.

Table 4 reports the empirical findings. While the density of skilled foreigners exerts a positive and statistically significant effect on innovation, the diversity of skilled and un-skilled migrants fails to exert a significant effect. This finding may be due to the limitation described above. For this reason, we apply only the share of skilled foreigners as a measure of diversity in the remaining estimations.

5. Robustness Checks

5.1 Occupation and education mismatch

As discussed above, we employ in this analysis an unconventional measure of skill for the diversity variable. We believe that a measure of skill based on occupation rather than education may better capture the effective contribution of foreigners to the creation of knowledge. The distinction between occupation and education skills is relevant particularly for foreigners, as high education attainments do not guarantee that migrants are employed in high skill occupations. Therefore, as a robustness check, we compute the share of skilled migrants according to their educational attainment. In ELFS the information of the highest level of education completed is available, codified using the International Standard Classification of Education (ISCED). We define highly educated migrants those with tertiary education and compute the share with respect to the highly educated population.[19]

The correlation between the share of skilled migrants and the share of highly educated migrants is very high, reaching 0.90. This is a first inspection on how effectively qualified foreigners are employed in the labour market, according to the ELFS. It should be noted that a large portion of mismatching is not really captured in this dataset on regular immigration, as overeducation will disproportionally affect irregular immigrants. The high correlation of the variables indicates that countries that display a large share of skilled foreigners display a high share of qualified foreigners, and vice versa. In Figure 3, we plot the share of highly educated foreigners against the share of highly skilled foreigners, computed as a mean over the period. Countries below the 45 degree line are showing a mismatch between education attainments and employment. In relative terms, Finland, United Kingdom, Belgium and the Slovak Republic are the most virtuous countries, as they show a correspondence between the share of highly educated migrants and that of highly skilled migrants. On the contrary, a gap between the education and the occupation share exists in

[19] Tertiary education corresponds to level 5 and above of the ISCED classification.

countries such as Greece, Italy, Iceland, the Czech Republic, Portugal and Ireland. These countries display a disproportional larger share of highly educated migrants compared to highly skilled migrants, suggesting a relatively inefficient allocation of qualified migrants in the labour market. However, these are almost tiny discrepancies as an overall look indicates that all countries are dispersed along or slightly below the 45 degree lines.

This issue is further inspected through a regression analysis. We replace our diversity measure with a diversity share computed in terms of education. We believe that the comparison of the estimated coefficients of the diversity variable in the base regression and in the additional regression provides two advantages. First, it helps understanding if an eventual mismatch in the allocation of skills in the labour market has an effect on the capacity to innovate. Second it indicates if the use of one measure in place of the other can mislead the empirical findings.

Table 5 reports the results of the new specification. The coefficients of the education-based diversity variable are positive and statistically significant in the patent specification. In the citation specification the coefficient is statistically significant only in the 2SLS. The elasticities of diversity computed along the skill dimension and the education dimension are quite similar in magnitude.[20] This finding indicates, first, that regardless of where educated migrants are employed, they contribute to the creation of knowledge. The competence acquired through education generates positive externalities that spill above the occupations they are employed in. Second, it indicates that the mismatch in qualification and occupation among highly skilled migrants is relatively small. The empirical relationship between diversity and innovation is robust to the alternative way in which the diversity measure is computed.

The existence of a mismatch between workers' education attainment and occupation employment has been analysed both for North America and Europe (Hartog, 2000). Even if an imperfect allocation of educational resources is a typical feature of the labour market for all workers, the problem affects immigrants to a larger extent. Moreover, despite an imperfect mismatch is characterised by an over-education and an under-education problem, migrants tends to disproportionately experience the former phenomenon. This is partially due to the imperfect transferability of skills and the imperfect screening of the quality of a foreign educational institution. This large body of research has produced different methodologies to identify the existence of a mismatch. Different approaches are commonly applied. One is called the "normative" approach, which measures the correspondence between education and qualification levels. A second is called "statistical" method. It assumes that each occupation is characterised by a "usual" education level, computed as the mean or the mode of the education of workers in each occupation. Over-qualification occurs if the worker faces a surplus in education compared to the usual level. A third method considers the experts' opinion regarding education requirements for each occupation and finally, the "self-declared" method exploits own workers evaluation of the education-occupation match.

[20] Only in one specification over four the difference in the coefficients is statistically significant at 10 percent.

To incorporate the issue of education mismatch in the present analysis, we interact the core diversity variable with a variable that measures the rate of migrants' over qualification. We adopt a ranking of OECD countries, which employs a normative-type approach (OECD, 2007). These over-qualification rates indicate the proportion of foreigners who are over-qualified and are computed measuring the correspondence between the level of education and job qualifications. Over-qualified are migrants who own upper secondary education or above and are employed in elementary occupations as well as foreigners with tertiary education employed in intermediate skill occupations (second skill occupations according to Table 1). Two rankings are available. The first is computed from survey data and the second from Censuses and Population Registers. We define a country as an "effective allocation" one if its over-qualification rate among migrants is below the sample median.[21] Table 6 reports the estimated results, where diversity computed according to the skill dimension is interacted with the effective allocation dummy. The 2SLS regressions indicate that a sound allocation of resources ensures a positive gain of diversity. In countries that display low over-qualification rates among migrants, diversity is associated with higher patent applications and citations levels. The result holds irrespective to the rankings adopted, whether based on censuses and population registers or survey data. On the contrary, countries that have over-qualification rates above the sample median do not gain from high diversity.

5.2 Migration Policy

Different contributions document that both the size and the composition of the international migration flows respond to national migration laws. Less restrictive policies are found to largely increase immigration (Mayda and Patel, 2004; Ortega and Peri, 2009). Moreover, migration policies targeted to highly educated migrants influence positively the skill selection of foreigners, by increasing the share of highly educated migrants (Peri, 2010). In this paper we extend the analysis to identify whether pro-skill migration policies influence innovation, through their effect on migration flows. Enlarging the pool of human capital available, these policies may represent an indirect determinant of innovation.

For this purpose, we compute an index that captures the loosening of national migration policies. We extended the database on immigration reforms in European countries, initially computed by Mayda and Patel (2004) and subsequently updated by Ortega and Peri (2009). We enlarged the dataset both in terms of country coverage and in terms of time spell. The database from Ortega and Peri refers to the period 1980-2005 and include 14 OECD countries. The new database contains immigration information for 24 European countries in the period 1995-2007. We focus uniquely on reforms regarding the entry of migrants and exclude policies that modify the stay of migrants. We also exclude any reform targeted to asylum-seekers. Moreover, given the focus of our paper, we restrict to reforms targeted to skilled workers.

[21] Data for Iceland in both cases is not available. Moreover, we always use the Census ranking for Poland and the Slovak Republic and the survey ranking for Belgium, Germany, Netherlands and Norway since it is the only data available.

After collecting these migration laws we codify an index following Ortega and Peri (2009). We assign a value of 1 whenever the country reforms its migration law in the direction of easing access of skilled migrants. We then cumulate the assigned values over time. The index thus obtained ranges from a minimum value of 0 to a maximum value of 3. Figure 4 plots the migration policy variable, for the different countries in the sample. Two features emerge. First, it is clear that there are countries that barely adopt reforms favouring highly educated migrants. Belgium, Denmark, Spain and Sweden, for example, applied no pro-skill reforms in the period considered. On the contrary Austria, Czech Republic, Finland, France, Germany and Slovak Republic show a clear and continue attempt to attract skilled migration by promoting a plurality of reforms of this type. The majority of countries implemented only one reform in the entire period (Greece, Hungary, Ireland, Italy, Netherlands, Norway, Poland, Portugal and UK). Second, the graph shows these reforms were mainly implemented after 2000. An exception is Austria, which anticipates slightly the adoption of laws supporting skilled immigration.

In the empirical analysis we interact the key diversity variable with the policy index. The objective is to identify if diversity has a larger effect on innovation in countries that put in place selective migration policies pro-skilled migrants. In Europe most schemes in favour of highly skilled migration are "employer-driven", in that a highly skilled foreigner is admitted only if she already received a job offer (Chaloff and Lemaitre, 2009; Bertoli et al., 2009). This implies a better match between skill demand and supply, also among foreigners.

We adopt three different ways to split the countries according to their propensity to implement pro-skilled migration policies, and thus we build three different interactions indicators. The first approach identifies three groups, namely nations that implement no pro-skill reforms, minimum number of reforms, or several reforms. The second and third approaches define only two groups. In the second approach we distinguish between countries that never implemented any pro-skill reform from those that implemented at least one. In the third approach we distinguish between countries that put in place more than one pro-skilled migration law from those that implemented zero or only one reform.[22]

The empirical findings, presented in Table 7 and 8 for patents and citations, respectively, are as follows. First, in the patent specification no gains emerge from the application of pro-skill migration reforms. The coefficient of the interaction term in the patent specification is never statistically different from zero. Second, countries that design pro-skilled migration laws display a positive relation between diversity and the number of citations, irrespective to the number of reforms implemented. On the contrary, diversity has a null effect on the number of citations in countries that apply no reforms. A clear distinction emerges between countries that never put in place reforms and those that adopted one or more. A positive and significant coefficient of

[22] The original policy variable, which is time variant, has not been introduced in its original form, given that it may be endogenous. It is documented that countries allow for a larger number of foreigners in boom times, whereas they are more stringent in issuing visas in time of recessions. The variables used in the estimation on the contrary, being time-invariant, should not suffer for endogeneity.

the interaction term results both in column (2) and in column (3), which apply the first and second approach. On the contrary, if one applies the third approach and distinguishes between countries that implement many reforms from those that apply one or none, no gain emerges from diversity.

5.3 Additional robustness checks

To avoid misspecification due to omitted variables bias we include in the estimated specification some additional controls that may enter a knowledge production function. In agreement with Niebuhr, we include a measure of the industrial structure of the countries, computed as the ratio between the manufacturing and the service value added. The sectoral composition influences the propensity of patenting, as far as countries with a larger manufacturing sector compared to service should patent relatively more. We add also an additional control for the size of the country, through the variable population. We believe that the stock of the skilled labour force already serves as a proxy for country size, but it is also true that the skill composition of the labour force varies countries by countries, with some having a disproportional larger share of skills in the population. Results are reported in Table 9. The empirical findings suggest that our basic specification does not suffer from omitted variable bias, as far as the key controls have significant coefficients, whereas additional controls fail to exert a significant impact on innovation.

In the present specifications we assume a limited delay in the response of the dependent variable to changes in the explanatory variables. As a robustness check, we assume a slower response of the dependent variable and employ two to four years lag in the controls. Tables 10 and 11 report the estimated coefficients. The coefficients of the diversity variable and of the stock of knowledge are robust to these specifications.

The knowledge stock is computed applying yearly intramural R&D expenditure. An alternative approach uses the number of patents as the main input of the perpetual inventory formula, described in equation (3). The results of this alternative specification are presented in Table 12. The coefficients of diversity and of the knowledge stock do not display significant changes.

The number of citations is calculated as the sum of all dates citations received by documents published in a specific year. This implies that citations for recent years are truncated, since recent publications have less time to accumulate citations. The use of year fixed effects should avoid biases in the coefficients. However, as a robustness check, we drop the last observations of the panel. We first regress the number of citations by documents on a set of year dummy variables. The coefficients of the year dummies are stable till 2003 and then drops. This finding suggests that citations occur within few years after an article is published and older articles are less likely to be cited. Therefore, truncation seems to be more problematic only after 2004. For this reason we run the estimation only for citations of articles published between 1995 and 2003. Table 13 presents the result. The coefficient of ethnic diversity in the 2SLS is still positive and statistically significant, although it decreases in magnitude.

As an additional robustness check we use the number of documents published during a specific year, and the number of citable documents, with the latter comprising exclusively articles, reviews and conference

papers. The beneficial effect of diversity is robust to the use of different proxies for innovation in general knowledge, as indicated by the 2SLS coefficients of Table 14.

An additional check is to capture if some destination countries, by means of a better proficiency in an international foreign language, may better exploit complementarities with foreigners. Barriers to communication may hinder potential externalities. To capture this aspect, we distinguish destinations on the basis of the ability of country national to speak an international language such as English. Data are taken from a Eurobarometer survey, carried out in 2005, where respondents were asked about their skills in foreign languages. Based on the results of the survey, EU countries are ranked according to the percentage of nationals who are able to speak English. We define an English proficiency dummy equal to one for countries with a percentage above the sample median and zero for countries below the sample median. We then interact the dummy with the diversity variable. Table 15 reports the empirical findings. The table shows that language barriers hinder potential externalities, being the coefficient of the interaction term positive and statistically significant and the coefficient of the diversity variable not statistically significant.

6. Conclusion

In this paper we employ a simple model where the innovation production function depends on the stock of knowledge, on the number of people employed in the research sector and on cultural diversity. We provide two proxies for the innovative capacity of country, namely the number of patents and the number of citations to published articles. The first is a widely adopted measure and captures patentable, applied knowledge, whereas the second is a better indicator of general knowledge in society. In the sample of 20 European countries considered the two measures display a high correlation.

The empirical results indicate that the stock of existing knowledge has a positive effect on innovation. This drives in favour of the "standing on shoulders" assumption, as far as the accumulation of past knowledge increases the creation of new knowledge. Second a larger pool of innovators boosts the production of knowledge, despite the coefficient turned not statistically significant in some specifications. Third, a positive impact of cultural diversity on the innovative capacity of the recipient countries emerges. This result reinforces the ideas that complementarities exist between natives and foreigners. Foreigners might positively affect natives' productivity, as new ideas are likely to arise through the interaction of diverse cultures and diverse approaches in problem solving. Not only high skill immigrants display high rates of patenting, but they also allow natives to produce greater innovation.

An additional control is added in the estimation in order to capture the existence of knowledge spillovers from one country to another. Contrary to predictions, external knowledge seems to have a null effect on domestic innovation. This point certainly needs further investigation

In this analysis we employ an unconventional measure of skill for the diversity variable. Rather than measuring education skills we capture occupation skills. As a robustness check, we test whether diversity is robust to the way we measure skills. We find that the elasticities of diversity computed according to the two

alternative skill measures are highly comparable. This finding may indicate, first that regardless of where educated migrants are employed, they contribute to the creation of knowledge. The competence acquired through education generates positive externalities that spill above the occupations they are employed in. Second it indicates that the mismatch in qualification and occupation among highly skilled legal migrants is relatively small. We also find that countries that are relatively more efficient in allocating highly educated foreigners into highly skilled occupations have a true gain in terms of higher innovative capacity. Moreover, countries that design pro-skilled migration laws display a positive relation between diversity and the number of citations, irrespective to the number of reforms implemented. Finally, better language communication between foreigners and nationals favour the positive externalities of ethnic diversity.

The analysis is robust to the inclusion of additional control variables, to the use of a longer lags in response of the control variables, to alternative proxies for the stock of available knowledge, the pool of qualified labour force, and innovation in general knowledge.

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Figures and Tables

Figure 1: Patents and Citations, average 1995-2008

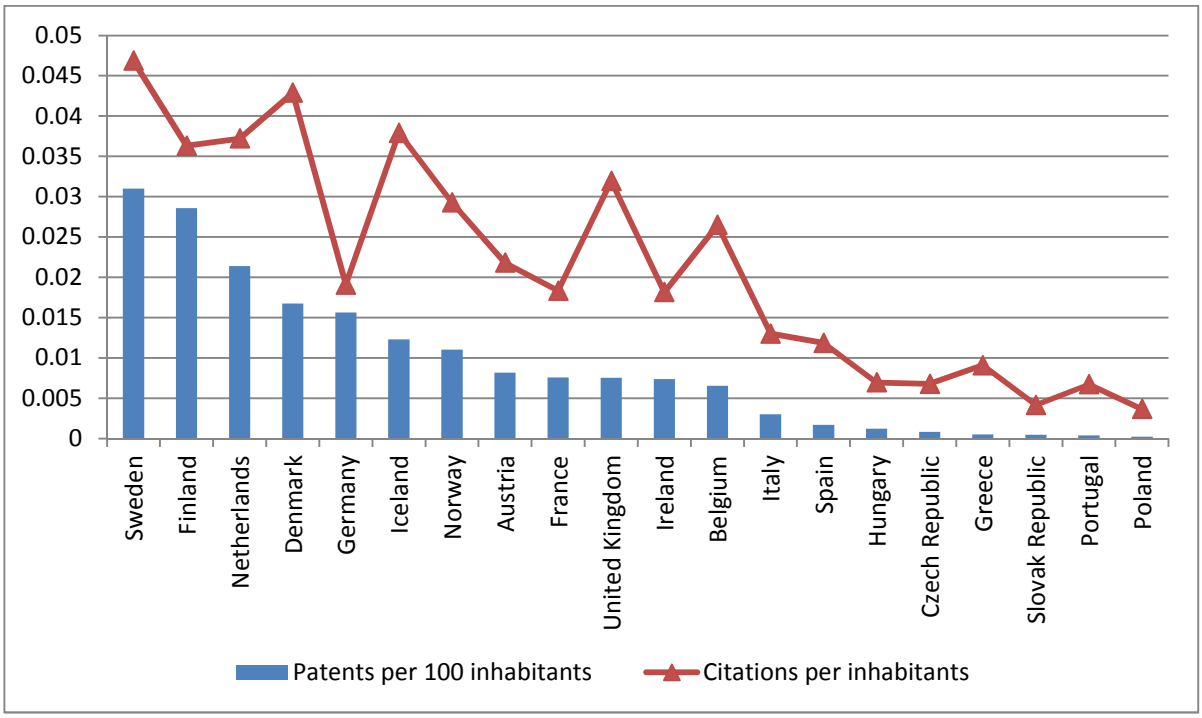

Figure2: Share of foreigners and skilled foreigners (%)-Census 2001

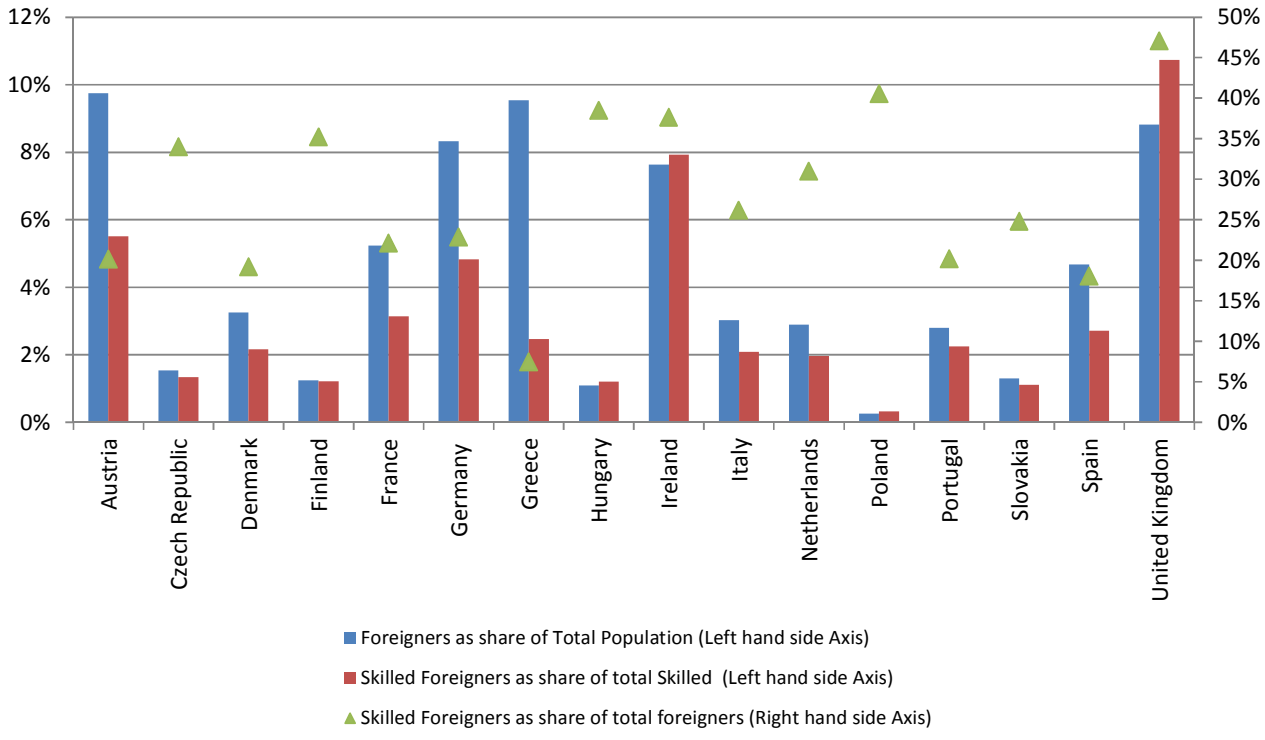

Figure 3: Share of highly educated versus highly skilled foreigners

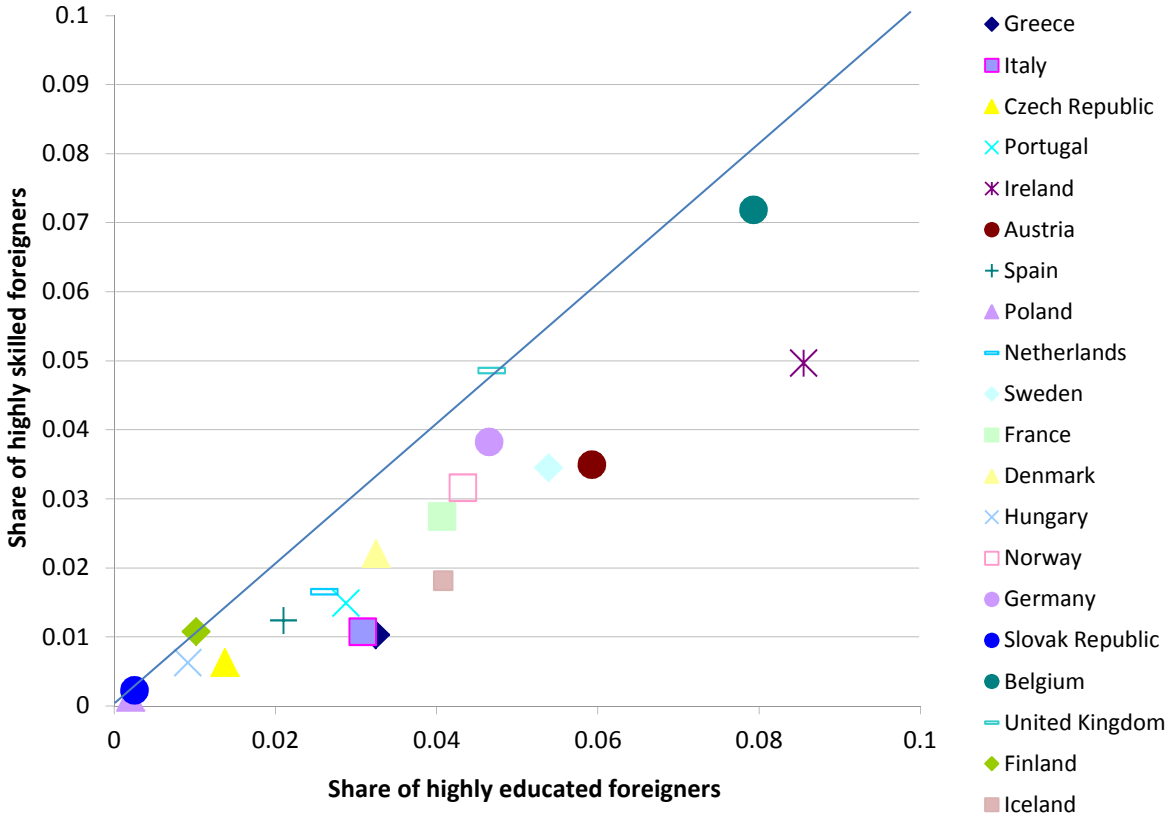

Figure 4: European migration policies targeted to skilled labour: 1995-2007

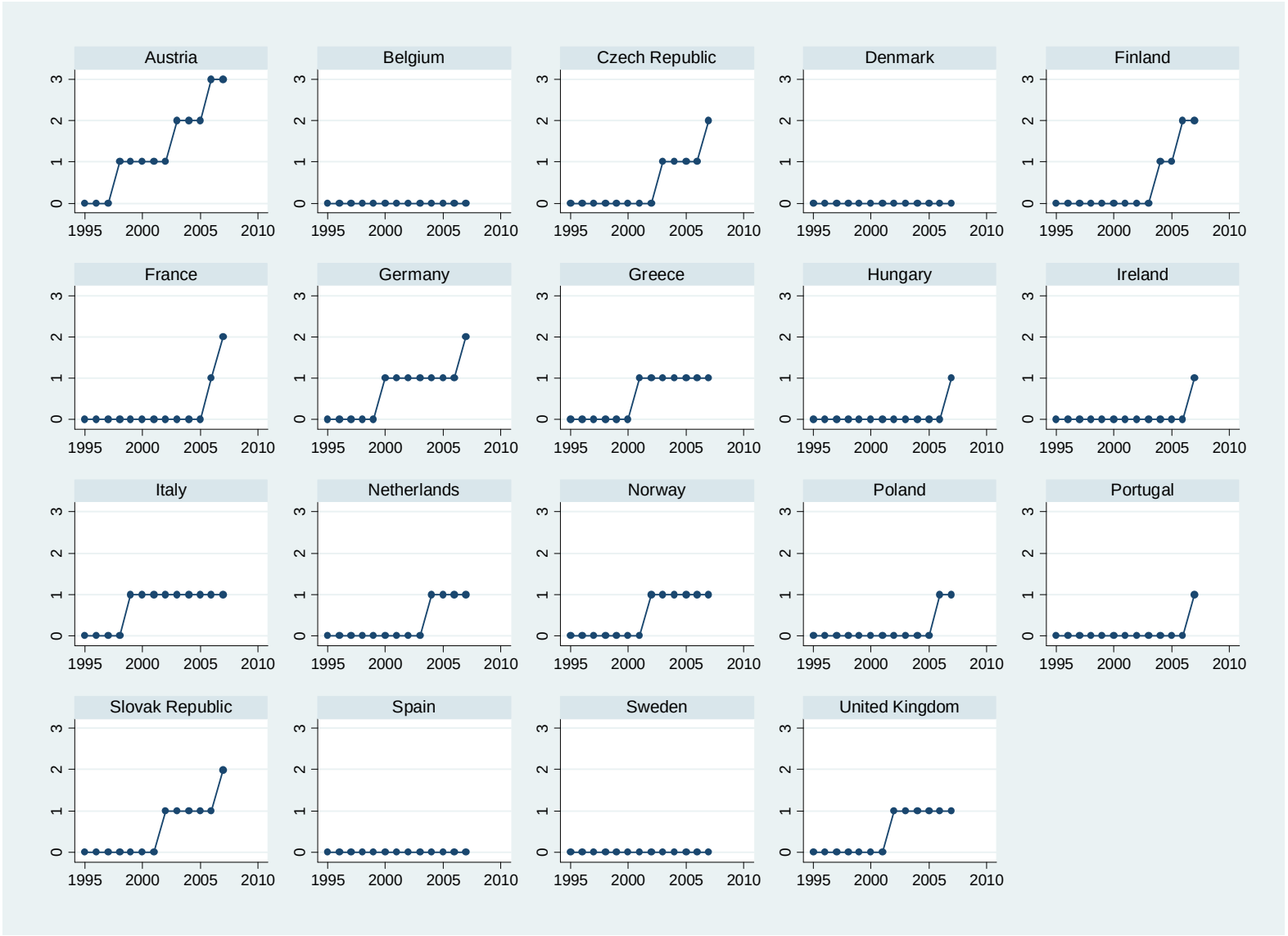

Table 1: Definitions of the four ISCO skill levels

Skill Level	ISCO Occupation	Description
First	9. Elementary occupations	They require the performance of simple and routine physical or manual tasks. Many occupations at Skill Level 1 may require physical strength and/or endurance. For some jobs basic skills in literacy and numeracy may be required. If required these skills would not be a major part of the job. For competent performance in some occupations at Skill Level 1, completion of primary education or the first stage of basic education (ISCED Level 1) may be required. A short period of on-the-job training may be required for some jobs.
Second	4. Clerks; 5. Service workers and shop and market sales workers; 6. Skilled agricultural and fishery workers; 7. Craft and related trades workers; 8. Plant and machine operators and assemblers	They involve the performance of tasks such as operating machinery and electronic equipment; driving vehicles; maintenance and repair of electrical and mechanical equipment; and manipulation, ordering and storage of information. For almost all occupations at Skill Level 2 the ability to read information such as safety instructions, to make written records of work completed, and to accurately perform simple arithmetical calculations is essential. Many occupations at this skill level require relatively advanced literacy and numeracy skills and good interpersonal communication skills. In some occupations these skills are required for a major part of the work. Many occupations at this skill level require a high level of manual dexterity. The knowledge and skills required for competent performance in all occupations at Skill Level 2 are generally obtained through completion of the first stage of secondary education (ISCED Level 2). Some occupations require the completion of the second stage of secondary education (ISCED Level 3), which may include a significant component of specialised vocational education and on-the-job training. Some occupations require completion of vocation specific education undertaken after completion of secondary education (ISCED Level 4). In some cases experience and on the job training may substitute for the formal education.
Third	3. Technicians and associate professionals	They involve the performance of complex technical and practical tasks which require an extensive body of factual, technical and procedural knowledge in a specialised field. Occupations at this skill level generally require a high level of literacy and numeracy and well developed interpersonal communication skills. These skills may include the ability to understand complex written material, prepare factual reports and communicate with people who are distressed. The knowledge and skills required at Skill Level 3 are usually obtained as the result of study at a higher educational institution following completion of secondary education for a period of 1 – 3 years (ISCED Level 5b). In some cases extensive relevant work experience and prolonged on the job training may substitute for the formal education.
Fourth	1. Legislators, senior officials and managers; 2. Professionals	They involve the performance of tasks which require complex problem solving and decision making based on an extensive body of theoretical and factual knowledge in a specialised field. The tasks performed include analysis and research to extend the body of human knowledge in a particular field, diagnosis and treatment of disease, imparting knowledge to others, design of structures or machinery and of processes for construction and production. Occupations at this skill level generally require extended levels of literacy and numeracy, sometimes at a very high level, and excellent interpersonal communication skills. These skills generally include the ability to understand complex written material and communicate complex ideas in media such as books, reports and oral presentations. The knowledge and skills required at Skill Level 4 are usually obtained as the result of study at a higher educational institution for a period of 3 – 6 years leading to the award of a first degree or higher qualification (ISCED Level 5a or higher). In some cases experience and on the job training may substitute for the formal education. In many cases appropriate formal qualifications are an essential requirement for entry to the occupation.

Source: International Standard Classification of Occupations (ISCO-08) – Conceptual Framework-Annex1

Table 2: Distribution of workers into skill groups-2008-EU 27-%

	Skill1	Skill2	Skill3	Skill4
Employed persons, 15-64 years old	9.8	51.4	16.5	22.2

Source: Eurostat, Statistics Database

Table 3: The effect of diversity on innovation –OLS and 2SLS

	Patents		Citations	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
ln(diversity)	0.131**	0.333**	0.136**	0.312***
	[0.0620]	[0.152]	[0.0507]	[0.0961]
ln(stock of total R&D)	0.602*	0.557***	0.423*	0.384***
	[0.299]	[0.170]	[0.223]	[0.102]
ln(skilled labour force)	0.454*	0.459**	0.211	0.216**
	[0.246]	[0.208]	[0.183]	[0.104]
Observations	213	213	213	213
Number of countries	20	20	20	20
F-test 1st stage	-	22.86	-	22.86

Notes: In columns (1) and (2) the dependent variable is the natural logarithm of the patent applications filed under the PCT recorded by priority date; in columns (3) and (4) is the natural logarithm of the number of citations. Country dummies and year dummies are included in all specifications. * denotes significant at 10%; ** significant at 5%; *** significant at 1%. Heteroskedasticity robust standard errors in parentheses. The excluded instrument in the first stage of the 2SLS is the log of imputed shares.

Table 4: The effect of diversity on innovation, Herfindahl Index

	Patents		Citations	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
ln(diversity)	0.111*	0.304**	0.116**	0.295**
	[0.0629]	[0.148]	[0.0476]	[0.120]
ln(stock of total R&D)	0.630*	0.528**	0.43	0.336**
	[0.316]	[0.211]	[0.255]	[0.140]
ln(skilled population)	0.376	0.377*	0.184	0.185*
	[0.218]	[0.209]	[0.173]	[0.104]
Ln(Herfindahl)	0.539	0.345	0.353	0.172
	[0.478]	[0.249]	[0.370]	[0.187]
Observations	183	182	183	182
Number of countries	17	17	17	17
F-test 1st stage	-	15.03	-	15.03

Notes: The dependent variable in columns (1) and (2) is the natural logarithm of the patent applications filed under the PCT recorded by priority date; in columns (3) and (4) is the natural logarithm of the number of citations. Country dummies and year dummies are included in all specifications. * denotes significant at 10%; ** significant at 5%; *** significant at 1%. Heteroskedasticity robust standard errors in parentheses. The excluded instrument in the first stage of the 2SLS is the log of imputed shares.

Table 5: Alternative skill measure- education attainment

	Patents		Citations	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
ln(diversity_edu)	0.129*	0.452***	0.0522	0.205*
	[0.0708]	[0.175]	[0.0455]	[0.114]
ln(stock of total R&D)	0.492	0.388**	0.469	0.419***
	[0.363]	[0.185]	[0.275]	[0.128]
ln(skilled labour force)	0.312	0.0808	0.203	0.0940
	[0.319]	[0.320]	[0.217]	[0.157]
Observations	207	207	207	207
Number of countries	20	20	20	20
F-test 1st stage	-	22.05	-	22.05

Notes: In columns (1) and (2) the dependent variable is the natural logarithm of the patent applications filed under the PCT recorded by priority date; in columns (3) and (4) is the natural logarithm of the number of citations. Country dummies and year dummies are included in all specifications. * denotes significant at 10%; ** significant at 5%; *** significant at 1%. Heteroskedasticity robust standard errors in parentheses. The excluded instrument in the first stage of the 2SLS is the log of imputed shares.

Table 6: The effect of diversity on innovation, by effective allocation

	Patents				Citations			
	Survey Data		Census and registers		Survey Data		Census and registers	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(diversity)	0.0582	0.224	0.0601	0.195	0.0211	0.118	0.0241	0.0635
	[0.0822]	[0.153]	[0.0876]	[0.164]	[0.0614]	[0.0957]	[0.0659]	[0.105]
ln(diversity)*effective allocation	0.277	0.442**	0.28	0.520***	0.264*	0.314***	0.263*	0.447***
	[0.197]	[0.195]	[0.209]	[0.199]	[0.128]	[0.109]	[0.131]	[0.108]
ln(stock of public R&D)	0.53	0.455**	0.532	0.459**	0.483*	0.446***	0.485*	0.448***
	[0.364]	[0.198]	[0.365]	[0.198]	[0.271]	[0.116]	[0.271]	[0.114]
ln(skilled labour force)	0.518**	0.584***	0.513**	0.611***	0.373**	0.390***	0.368**	0.446***
	[0.214]	[0.215]	[0.212]	[0.210]	[0.140]	[0.0954]	[0.139]	[0.0889]
Observations	200	200	200	200	200	200	200	200
Number of countries	19	19	19	19	19	19	19	19
F-test 1st stage								
ln(diversity)	-	11.02	-	10.35	-	11.02	-	10.35
ln(diversity)*effective allocation	-	12.87	-	17.11	-	12.87	-	17.11

Notes: In columns (1) to (2) the dependent variable is the natural logarithm of the patent applications filed under the PCT recorded by priority date; in columns (5) to (8) is the natural logarithm of the number of citations. Country dummies and year dummies are included in all specifications. * denotes significant at 10%; ** significant at 5%; *** significant at 1%. Heteroskedasticity robust standard errors in parentheses. The excluded instrument in the first stage of the 2SLS is the log of imputed shares. In columns (1), (2), (5) and (6) the effective allocation dummy is computed from survey data; in columns (3), (5), (7) and (8) the effective allocation dummy is computed from censuses and population registers. The effect of the effective allocation dummy alone is absorbed by the country fixed effects.

Table 7: The effect of diversity on innovation, by skilled migration policies. Patents

	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
ln(diversity)	0.561*	0.767**	0.332	0.519**	0.337*	0.659**
	[0.319]	[0.343]	[0.244]	[0.226]	[0.181]	[0.260]
ln(diversity)*skilled policy	-0.149	-0.14	-0.183	-0.148	-0.229	-0.301
	[0.114]	[0.111]	[0.266]	[0.218]	[0.214]	[0.217]
ln(stock of total R&D)	0.517	0.447**	0.531	0.464**	0.514	0.423**
	[0.372]	[0.205]	[0.387]	[0.205]	[0.362]	[0.199]
ln(skilled labour force)	0.249	0.243	0.281	0.288	0.304	0.263
	[0.301]	[0.274]	[0.274]	[0.261]	[0.275]	[0.269]
Observations	200	200	200	200	200	200
Number of countries	0.772	0.755	0.769	0.754	0.772	0.749
F-test 1st stage						
ln(diversity)	-	11.79	-	11.09	-	12.17
ln(diversity)*skilled policy	-	8.90	-	22.67	-	19.28

Notes: The dependent variable is the natural logarithm of the patent applications filed under the PCT recorded by priority date; country dummies and year dummies are included in all specifications. * denotes significant at 10%; ** significant at 5%; *** significant at 1%. Heteroskedasticity robust standard errors in parentheses. The excluded instrument in the first stage of the 2SLS is the log of imputed shares. In columns (1) and (2) the skilled migration variable ranges from 1 to 3. In columns (3) and (4) the skilled migration variable is a dichotomous variable, which is equal one if the countries put in place at least one pro-skilled migration reforms and 0 otherwise. In columns (5) and (6) the skilled migration variable is a dichotomous variable, which is equal one if the countries put in place more than one pro-skilled migration reforms and 0 if it introduced zero or only one reform in the period considered. The effect of the skilled policy variable alone is absorbed by the country fixed effects.

Table 8: The effect of diversity on innovation, by skilled migration policies. Citations

	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
ln(diversity)	0.271	-0.170	-0.0441	-0.111	0.277*	0.209
	[0.324]	[0.212]	[0.150]	[0.114]	[0.150]	[0.144]
ln(diversity)*skilled policy	-0.055	0.170*	0.192	0.530***	-0.204	0.0573
	[0.115]	[0.0870]	[0.160]	[0.143]	[0.176]	[0.155]
ln(stock of total R&D)	0.481*	0.463***	0.493*	0.430***	0.468	0.455***
	[0.276]	[0.131]	[0.265]	[0.131]	[0.273]	[0.125]
ln(skilled labour force)	0.195	0.389**	0.352*	0.525***	0.174	0.257*
	[0.235]	[0.159]	[0.179]	[0.143]	[0.219]	[0.137]
Observations	200	200	200	200	200	200
Number of countries	0.786	0.735	0.789	0.721	0.795	0.762
F-test 1st stage						
ln(diversity)	-	11.79	-	11.09	-	12.17
ln(diversity)*skilled policy	-	8.90	-	22.67	-	19.28

Notes: The dependent variable is the natural logarithm of the number of citations. Country dummies and year dummies are included in all specifications. * denotes significant at 10%; ** significant at 5%; *** significant at 1%. Heteroskedasticity robust standard errors in parentheses. The excluded instrument in the first stage of the 2SLS is the log of imputed shares. In columns (1) and (2) the skilled migration variable ranges from 1 to 3. In columns (3) and (4) the skilled migration variable is a dichotomous variable, which is equal one if the countries put in place at least one pro-skilled migration reforms and 0 otherwise. In columns (5) and (6) the skilled migration variable is a dichotomous variable, which is equal one if the countries put in place more than one pro-skilled migration reforms and 0 if it introduced zero or only one reform in the period considered. The effect of the skilled policy variable alone is absorbed by the country fixed effects.

Table 9: The effect of diversity on innovation, additional control variables

	Patents		Citations	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
ln(diversity)	0.139***	0.332**	0.130***	0.373***
	[0.0436]	[0.141]	[0.0424]	[0.0980]
ln(stock of total R&D)	0.563	0.504**	0.315	0.240*
	[0.372]	[0.210]	[0.272]	[0.129]
ln(skilled labour force)	0.457**	0.455**	0.139	0.137
	[0.202]	[0.215]	[0.158]	[0.120]
ln(industrial structure)	-0.0644	-0.0841	0.0852	0.0603
	[0.458]	[0.300]	[0.249]	[0.168]
ln(Pop)	1.144	0.951	0.271	0.0266
	[2.362]	[1.350]	[1.617]	[0.927]
Observations	197	197	197	197
Number of countries	20	20	20	20
F-test 1st stage		21.22		21.22

Notes: In columns (1) to (2) the dependent variable is the natural logarithm of the patent applications filed under the PCT recorded by priority date; in columns (3) to (4) is the natural logarithm of the number of citations. Country dummies and year dummies are included in all specifications. * denotes significant at 10%; ** significant at 5%; *** significant at 1%. Heteroskedasticity robust standard errors in parentheses. The excluded instrument in the first stage of the 2SLS is the log of imputed shares.

Table 10: The effect of diversity on innovation, two to four years lag. Patents

	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
ln(diversity)	0.152	0.472***	0.0548	0.524***	0.0392	0.564***
	[0.0963]	[0.170]	[0.0770]	[0.153]	[0.0671]	[0.156]
ln(stock of total R&D)	0.659*	0.571***	0.430	0.284	0.534**	0.331*
	[0.323]	[0.198]	[0.282]	[0.211]	[0.246]	[0.196]
ln(skilled labour force)	0.270	0.316	0.294	0.451***	-0.0248	0.26
	[0.332]	[0.263]	[0.268]	[0.149]	[0.348]	[0.172]
Observations	194	194	175	174	155	154
Number of countries	20	20	19	19	19	18
F-test 1st stage	-	21.08	-	18.05	-	16.08

Notes: The dependent variable is the natural logarithm of the patent applications filed under the PCT recorded by priority date. In columns (1) and (2) we assume two years lags, in columns (3) and (4) three years lags and in columns (5) and (6) four years lags. Country dummies and year dummies are included in all specifications. * denotes significant at 10%; ** significant at 5%; *** significant at 1%. Heteroskedasticity robust standard errors in parentheses. The excluded instrument in the first stage of the 2SLS is the log of imputed shares.

Table 11: The effect of diversity on innovation, two to four years lag. Citations

	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
ln(diversity)	0.0846	0.280***	0.0767	0.260***	-0.00809	0.172**
	[0.0512]	[0.0951]	[0.0476]	[0.0848]	[0.0726]	[0.0789]
ln(stock of total R&D)	0.408	0.354***	0.427*	0.369***	0.466**	0.397***
	[0.240]	[0.116]	[0.221]	[0.123]	[0.194]	[0.123]
ln(skilled labour force)	0.159	0.187*	0.0259	0.0872	-0.0364	0.0613
	[0.179]	[0.108]	[0.149]	[0.103]	[0.177]	[0.107]
Observations	194	194	175	174	155	154
Number of countries	20	20	20	19	19	18
F-test 1st stage	-	21.08	-	18.05	-	16.08

Notes: The dependent variable is the natural logarithm of the number of citations. In columns (1) and (2) we assume two years lags, in columns (3) and (4) three years lags and in columns (5) and (6) four years lags. Country dummies and year dummies are included in all specifications. * denotes significant at 10%; ** significant at 5%; *** significant at 1%. Heteroskedasticity robust standard errors in parentheses. The excluded instrument in the first stage of the 2SLS is the log of imputed shares.

Table 12: The effect of diversity on innovation, alternative measure for knowledge stock

	Patents	
	OLS	2SLS
	(1)	(2)
ln(diversity)	0.111***	0.348**
	[0.0345]	[0.155]
ln(stock of total Patents)	0.734***	0.694***
	[0.193]	[0.103]
ln(skilled labour force)	0.0311	0.0562
	[0.252]	[0.233]
Observations	213	213
Number of countries	20	20
F-test 1st stage		22.12

Notes: The dependent variable is the natural logarithm of the patent applications filed under the PCT recorded by priority date. Country dummies and year dummies are included in all specifications. * denotes significant at 10%; ** significant at 5%; *** significant at 1%. Heteroskedasticity robust standard errors in parentheses. The excluded instrument in the first stage of the 2SLS is the log of imputed shares.

Table 13: The effect of diversity on innovation, 1995-2003

	Citations	
	OLS	2SLS
	(1)	(2)
ln(diversity)	0.0338	0.180*
	[0.0605]	[0.0983]
ln(stock of total R&D)	0.549***	0.417***
	[0.154]	[0.120]
ln(skilled population)	-0.183	-0.0964
	[0.193]	[0.100]
Observations	118	117
Number of countries	18	17
F-test 1st stage	-	7.47

Notes: The dependent variable is the natural logarithm of the number of citations. Country dummies and year dummies are included in all specifications. * denotes significant at 10%; ** significant at 5%; *** significant at 1%. Heteroskedasticity robust standard errors in parentheses. The excluded instrument in the first stage of the 2SLS is the log of imputed shares.

Table 14: The effect of diversity on innovation, alternative measures of general knowledge

	Published Documents		Citable Documents	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
ln(diversity)	0.0715	0.128**	0.0769	0.145**
	[0.0432]	[0.0595]	[0.0445]	[0.0600]
ln(stock of total R&D)	0.462***	0.449***	0.462***	0.447***
	[0.140]	[0.0683]	[0.143]	[0.0704]
ln(skilled population)	0.127	0.129*	0.116	0.118
	[0.117]	[0.0711]	[0.118]	[0.0721]
Observations	213	213	213	213
Number of countries	20	20	20	20
F-test 1st stage		22.86		22.86

Notes: The dependent variable in columns (1) and (2) is the natural logarithm of the patent applications filed under the PCT recorded by priority date; in columns (3) and (4) is the natural logarithm of the number of citations. Country dummies and year dummies are included in all specifications. * denotes significant at 10%; ** significant at 5%; *** significant at 1%. Heteroskedasticity robust standard errors in parentheses. The excluded instrument in the first stage of the 2SLS is the log of imputed shares.

Table 15: The effect of diversity on innovation. Dummy for English proficiency

	Patents		Citations	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
ln(diversity)	-0.00062	-0.0425	0.0251	0.0465
	[0.0950]	[0.149]	[0.0687]	[0.160]
ln(diversity)*dummy for english proficiency	0.378**	0.674***	0.242*	0.275*
	[0.177]	[0.182]	[0.132]	[0.149]
ln(stock of total R&D)	0.383	0.264	0.419	0.397***
	[0.323]	[0.171]	[0.271]	[0.107]
ln(skilled population)	0.259	0.187	0.202	0.193*
	[0.240]	[0.245]	[0.209]	[0.114]
Observations	188	188	188	188
Number of countries	18	18	18	18
F-test 1st stage				
ln(diversity)	-	11.55		11.55
ln(diversity)*dummy for english proficiency	-	24.57		24.57

Notes: The dependent variable in columns (1) and (2) is the natural logarithm of the patent applications filed under the PCT recorded by priority date; in columns (3) and (4) is the natural logarithm of the number of citations. Country dummies and year dummies are included in all specifications. * denotes significant at 10%; ** significant at 5%; *** significant at 1%. Heteroskedasticity robust standard errors in parentheses. The excluded instrument in the first stage of the 2SLS is the log of imputed shares.

Appendix

Table A1: First Stage for the excluded instruments of cultural diversity

	ln(diversity)
	(1)
ln(Imputed shares)	0.337***
	[0.0704]
ln(stock of total R&D)	0.279*
	[0.152]
ln(skilled labour force)	-0.400**
	[0.189]
F-test of excluded instruments	F(1, 178) = 22.86
	Prob > F = 0.0000

Notes: * denotes significant at 10%; ** significant at 5%; *** significant at 1%. Heteroskedasticity robust standard errors in parentheses. All regressions include year and country fixed effects.