**Migration of Skilled Workers 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 bibliometric data, in a panel of 20 European countries between 1995 and 2008. The empirical findings show that a larger pool of migrants in the skilled professions is associated with higher levels of knowledge creation. Skilled migrants contribute both to the creation of "private" knowledge, measured by the number of patent applications through the Patent Cooperation Treaty, and to more "public" basic research, measured by the number of citations to published articles. This finding is robust, in that it uses both an occupation-based and an education-based index of skilled migration, as well as an instrumental variable estimation accounting for the endogeneity of the skilled migrants indicator and to a number of robustness checks. Our results suggest that policy efforts aiming at attracting skilled migrants to Europe and employing them in skilled professions, such as those put forward in the Europe 2020 Strategy, will indeed foster EU competitiveness in innovation.

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**Highlights**

- We study how skilled migrants impact knowledge formation in 20 European countries
- Skilled migrants positively contribute to both private and public knowledge creation
- Results are robust to the use of different proxies for innovation and migrants' share
- We confirm the positive role of past research investment

## 1. Introduction

Endogenous growth theory indicates that knowledge formation and the availability of better technologies have important repercussions on productivity and growth (Solow, 1957; Romer, 1990; Aghion and Howitt, 1992; Grossman and Helpman, 1994; Jones, 2009). A core contributor to the knowledge production function is a specialized labour force, namely highly skilled workers engaged in laboratories or in academia (Caballero and Jaffe, 1993; Kerr and Kerr, 2011). In addition to the level of education and the number of workers engaged in research, it is found that diversity in the research team is also a crucial ingredient in the innovation process (Kerr 2008, Stuen et al., 2012).

This paper combines the literature on innovation and knowledge production with the literature focusing on diversity, migration and productivity. We study how foreign skilled labour contributes to knowledge formation in Europe. This topic has been explored before, but mostly with a focus on the US market. This issue is however crucial in most EU member countries, which were once a "source" of migration, but are now increasingly seen as migration destinations for skilled and unskilled foreign workers (IOM, 2008).[1] The education level of recent flows of migrants has improved considerably over the past decade. Highly-educated foreigners exceed 31 million in the OECD area and account for 45% of the increase in the foreign born population (OECD, 2014). Indeed, attention has been increasingly drawn to the role of highly skilled immigration as a driver of technology development, innovation and economic performance (EMN, 2006; EC, 2007; EC, 2008).

The empirical evidence on whether and how skilled foreigners contribute to European knowledge formation is scarce.[2] Most of the literature on this topic 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 and Peri, 2012 among others). The few available macro-empirical analyses on European countries have a narrow geographical focus. Niebhur (2010) shows that ethnic diversity of skilled labour has a positive effect on patent applications, a common proxy for innovation, in German regions. Ozgen et al. (2011a) generalize these results for 170 NUTS2 regions in 12 Western European countries.[3]

The first aim of this paper is to fill this gap and provide new evidence in support of the positive contribution of skilled foreigners to innovation and knowledge production. We focus on a panel of 20 European countries, which includes historical members of the EU as well as Eastern European economies. The second new approach to our analysis is the use of two different proxies of innovative performance,

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

[2] Within the European context, papers have mostly concentrated on the static effect of diversity, namely the effect of migrants on native employment and wages (Dustmann et al, 2008; D'Amuri et al, 2010; Manacorda et al., 2006), the issue of skill-complementarity and task specialization (Cattaneo et al., 2013; D'Amuri and Peri, 2014) and the role of foreigners in fostering trade relations (Iranzo and Peri, 2009).

[3] The analysis of Ozgen et al. (2011a) is based on Austria, Belgium, Denmark, France, Western Germany, Ireland, Italy, the Netherlands, Portugal, Spain, Sweden and the UK.

patent applications and citations, for the purpose of exploring the effect of the foreign skilled labour force on the creation of private and public knowledge, respectively. The final contribution of our analysis is the use of two different dimensions for capturing the skills level of the foreign labour force. In the main part of our analysis we measure the skills level of foreigners by examining their actual occupation. We then check our results by following the general literature, which commonly measures skills by looking at examining the education level of foreigners.

One of the main concerns when estimating the effect of cultural and ethnic diversity on knowledge formation in the current framework is the endogeneity of migration flows. To address this issue appropriately, we employ an "ethnic enclave" instrumental variable. This approach, first suggested by Altonji and Card (1991) and largely used in the subsequent empirical literature (Card and DiNardo, 2000; Card, 2001; Peri and Sparber, 2009; Ottaviano et al., 2013; D'Amuri and Peri, 2014; Ottaviano and Peri, 2012) uses information on the pre-sample distribution of migrants and subsequent flows by area of origin to build imputed shares of migrants for each country.

As in the micro- analyses on this topic, we find a positive synergic interaction of diverse cultures and diverse approaches in problem solving. We show that foreign skilled labor exerts a positive effect on the innovative capacity of the recipient countries both for industrially applicable innovations and for more general abstract knowledge. This positive effect is confirmed independently of whether we measure skill by using a foreigner's education or occupation level. We reinforce the idea that complementarities exist between natives and foreigners. Skilled migrants employed in highly skilled jobs have a positive impact on innovation by increasing researchers' average productivity. The results we present hold true in a series of robustness checks, such as the inclusion of additional control variables, the use of longer lags, the use of different proxies for key explanatory variables, and the exclusion of certain countries from the sample.

The paper is organized as follows: Section 2 reviews the relevant literature; Section 3 presents a model of knowledge production function which highlights the role of diversity and details the methodology and data used in the empirical estimation. Sections 4 and 5 discuss the results and robustness checks, respectively. Section 6 concludes.

## 2. Literature Review

Hicks (1932), Schumpeter (1942) and Schmookler (1966) put forward the crucial hypotheses of induced technical change, creative destruction and the role of supply and demand determinants of innovation. Since then, the literature on knowledge creation and its contribution to growth has been vast. Important shaping forces for innovative capacity are 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). Great attention has also been given to the market failures which characterize knowledge production, namely the existence of inter-temporal, intersectoral and international spillovers (Jaffe, 1986; Coe and Helpman, 1995; Malerba, 1992; Branstetter, 2001; Mancusi, 2008).

Of paramount importance in R&D-based endogenous growth models is the knowledge production function, which is typically a function of the labour force in the research sector and of the available stock of knowledge (Romer 1990; Aghion and Howitt, 1992; Kortum, 1993; Grossman and Helpman, 1994; Abdih and Joutz, 2006). The larger the pool of researchers, the more innovative the given economy. The larger the knowledge stocks, the bigger the pool of discoveries and ideas that researchers can use to stand “on the shoulder of the giants” (Caballero and Jaffe 1993), with a positive effect on their productivity.

In addition, many contributions focus on the composition of the research labour force and its impact on knowledge formation. As research problems and technical bottlenecks become increasingly complex, the paradigm of solo geniuses has slowly been replaced by that of large teams and networks, bringing together diverse knowledge and perspectives (Hargadon, 2003, (Barabási, 2005, Jones, 2009). Team diversity can take different forms, from the background or ability of workers, to their age or gender, as well as their culture. The positive effect on productivity exerted by differences in ability and knowledge within the team members is rather uncontroversial (Hamilton et al., 2003 and Lazear, 1999). The effect of cultural and ethnic diversity is, conversely, more ambiguous. Younglove-Webb et al. (1999) and 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 successes stresses the positive contribution of permanent foreign staff as well as that of visiting scientists (Hollingsworth & Hollingsworth, 2000). Conversely, Bassett-Jones (2005) and Stahl et al. (2009) argue that team diversity imposes communication costs that might offset the creative benefits induced by complementarities among different team members. Very few studies using micro data focus on Europe and present conflicting results. In Parrotta et al. (2012), the innovation outcome of a sample of Danish firms increases in the skill and ethnic diversity of the workforce. These findings are, however, in contrast with those of Østegaard et al. (2011), which also focus on a sample of Danish firms, but conclude that ethnic diversity has no impact on innovative activity. Finally, Ozgen et al. (2011b) show that, overall, Danish firms which employ a relatively high share of foreigners are somewhat less innovative, with diversity being associated with higher product innovation only in a subsample of firms.

Building on these micro-founded concepts, the macro literature looks at highly skilled immigration flows and their dynamic implications for the innovative capacity of firms and universities. Results generally show that skilled foreign workers and higher diversity in research personnel are associated with more innovation and patenting activity. Chellaraj et al. (2008), Hunt and Gauthier-Loiselle (2010), Kerr and Lincoln (2010) and Peri (2007), for example, highlight the positive contribution of highly educated foreign-born workers and foreign graduate students to US patenting activities. Many other papers, such as Stuen et al. (2012) and Stephan and Levin (2001) analyse the contribution of foreign-born students and workers with different indicators of research performances, finding a disproportionally positive effect. Kerr (2008) and Kerr (2010) look into some of the mechanisms at the basis of this, such as the bridging role and the greater mobility of skilled workers working abroad.

As with micro data studies, most of these contributions focus on the USA, where immigrants represent a significant share of highly educated workers.[4] On the contrary, the impact of ethnic diversity on innovation in Europe is under-researched. To our knowledge, Niebhur (2010) and Ozgen et al. (2011a) constitute the only tests on the effect of ethnic diversity of skilled labour on EU innovation, as measured by patents. Both find that ethnic diversity has 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 setup, new ideas, $I$, are a function of the number of skilled workers employed in the research sector $S$ and of the average researcher productivity, $\bar{\delta}$ .

$$I = \bar{\delta} S \tag{1}$$

We assume that average productivity per researcher is a function of three key factors. The first is a measurement of resources invested in innovative activity $A$, which is proxied by a cumulative function of past innovation efforts. The higher $A$, the higher the historical investment in the production of new knowledge. The stock of knowledge of a given country impacts average productivity through inter-temporal spillovers. Researchers "stand on the shoulders of giants", namely they use previous knowledge as a stepping stone and improve the quality of innovation (Caballero and Jaffe, 1993; Stern et al., 2000).

The second factor affecting average productivity is the number of researchers, $S$, which captures potential decreasing returns. As the number of researchers in a country increases, negative congestion externalities arise in a given country, the so-called "stepping on toes" effect. Accidental or intentional duplication of efforts thus reduces the average productivity of R&D (Jones and Williams, 2000).

The third factor, which is the core interest of this paper, is an indicator of the share of migrants in the skilled labour forces, $D_s$ and proxies for ethnic diversity. As mentioned above, the role of diversity on innovation is ambiguous. By adding to the pool of skills in destination markets, skilled migrants are likely to positively affect the productivity of natives, as new ideas arise through the interaction of diverse cultures and diverse approaches to problem solving. However, the presence of migrants might also impose higher communication costs. Which effect prevails is a matter of empirical finding.

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

Hence $\bar{\delta}$ is defined as:

$$\bar{\delta} = (A)^{\alpha}\ (D_s)^{\beta}\ (S)^{\vartheta-1} \tag{2}$$

and equation (1) becomes:

$$I = (A)^{\alpha}\ (D_s)^{\beta}\ (S)^{\vartheta} \tag{3}$$

Equation (3) is the basis of the empirical analysis presented in this paper. Our interest lies in the estimation of β, which provides information on the impact of diversity on knowledge production, after checking for other confounding factors.

If we take the natural logarithm of equation (3) and explicitly introduce the country and time dimensions, the basic specification for each country *i* at time *t* becomes:

$$\ln(I_{i,t}) = \beta_0 + \beta_1 \ln(A_{i,t-1}) + \beta_2 \ln(D_{s_{i,t-1}}) + \beta_3 \ln(S_{i,t-1}) + \mu_t + \mu_i + \varepsilon_{i,t} \tag{4}$$

where $\mu_t$ is a set of year dummies; $\mu_i$ represents a set of country fixed effects and $\varepsilon_{i,t}$ is an idiosyncratic error term.[5] Equation (4) is estimated by using an unbalanced panel of 20 European countries from 1995 to 2008.[6] Both the sample of countries and the time period are limited by data availability.

In line with the literature, we use a one-year time lag of the independent variables to account for the time lag between the process of innovation and the codification of tangible or intangible outcomes of this process. In Section 5, we check the robustness of our results from the use of higher lags.

Finding a good proxy for innovation, $I$ has been the matter of much debate in the literature. Patent statistics are among the most commonly used. Patents are legal titles protecting a product or a process which are granted by a given patenting authority to the assignee.[7] Notwithstanding some limitations, the use of patent data as a proxy for innovation has been validated by a number of micro and macro studies (Griliches, 1990). Patents are linked to the output of the R&D process, and provide information on the number of technological blueprints available in any given market.

The most relevant shortcoming of patents in our context is that not all innovations are patented. Among other reasons, because of the way in which the patent system is constructed, a patent office grants temporary monopoly rights only to inventions which are industrially applicable. However, knowledge and innovation are a much broader concept than the count of patented blueprints. Therefore, a study based only on patents

[5] Focusing on 20 (developed) European countries, we never observe zero patents or citations during our sample period. Taking logs on both sides of equation (2) does not result in a loss of observations.

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

[7] 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 patent 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.

might not successfully capture all outcomes of the innovation process. Hence, to assess the role of diversity on all aspects of innovation production in Europe, we also focus on bibliometric data as an alternative measure of knowledge, one that is more strictly related to basic research.[8] The production of "public" knowledge is a key aspect of a country's innovativeness, one that might have more subtle but long-lasting effects on productivity and competitiveness. Indeed, a number of contributions look into the positive synergies between these public and private forms of knowledge indicators (publications and patents) for specific scientific sectors (Huang and Murray, 2009). The use of two proxies makes it possible not only 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 an inherently different nature.

A matter of concern when using patent and bibliometric data as proxies for innovation is to appropriately account for the quality of the new idea. For this reason, we carefully select two indicators which are closely related to high impact and high quality innovations. With respect to patent data, we exploit the design of the patent system to select our dependent variable. To protect a new idea, innovators can choose between different application "routes", which result in different patent rights. Specifically, an inventor can choose to apply for a patent 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 (PCT), thus eventually obtaining patent rights in more than one country.[9] Among these three options, PCT applications are more costly than applications to regional or national offices, and they represent those (higher quality) innovations that the inventor would like to exploit in more than one market (OECD, 2009).[10] We use PCT filings by inventors of each country in year *t* to measure industrially applicable innovation and thus provide a "quality threshold" which helps to weed out from our sample patents of "lower" quality.[11] Moreover, we count patents by priority date to ensure that each patent application is attributed to the year closest to the actual

[8] See Ducor (2000) for the use of both patents and citations in the definitions of the two faces of a country's knowledge.
[9] These "routes" are generally referred to as the national route, the regional route and 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 inventor's country). A second option for inventors is to submit a patent application to a regional office, such as the European Patent Office (EPO), 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 validates his or her rights. Alternatively, inventors 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 inventors to apply for patent rights in more than one jurisdiction. This is a very popular route among inventors targeting worldwide markets.
[10] In 2003 the (estimated) costs of a Euro-PCT (filing through PCT at the WIPO, designating the EPO) averaged around EUR 46,700, while the cost of obtaining a standard Euro-direct patent (direct filing to the EPO or extension of an earlier national patent application) was roughly EUR 30,530 (OECD, 2009).
[11] The use of unweighted "regional" and "international" routes patent data is common in the literature (Crepon and Duguet, 1997; Bottazzi and Peri, 2003; Peri, 2005a among others). An alternative approach would use information on patent family size, number of claims or forward citations to weight patent count data (OECD, 2009). However, the OECD database we have access to does not provide such information (OECD, 2011)

invention (OECD, 2009). Patent statistics are obtained from the OECD Patent Statistics Database (OECD, 2011).[12]

Regarding bibliometric data, we take into consideration the fact that intangible knowledge has a higher impact the more it is used to build upon in the creation of subsequent knowledge. Based on the assumption that publications which are more frequently cited are those of higher quality and impact, we use the count of aggregate 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). The number of citations informs us on how useful basic knowledge has been to other researches. Focusing on citations is thus tantamount to weighting each country's publications by a measure of quality. Bibliometric data comes from the SCImago Journal & Country Rank (SCImago, 2011). The variable is constructed as the number of citations (excluding self-citations) of all dates received by documents published in a given country in year *t*.[13] Calculating citations in this way results in a "truncation" of the citation function for the last years in the sample. The statistics are in fact not adjusted for the subsequent pool of possibly cited documents, which is clearly bigger for the older published documents. However, our analysis stops at 2008, while the SCImago aggregate data includes citations to all previous cohorts from articles published as late as 2011. Given that the citation function generally peaks after 4 to 5 years, we believe that using citation counts up to 2008 is reasonable. Moreover, time-fixed effects check the different average citation level received by each cohort of published articles.

The correlation between per capita PCT Patent applications and per capita citations in our sample is reasonably high, namely 0.80. This indicates that countries which are highly productive in patentable knowledge do well also in terms of general and more intangible knowledge (Figure 1).

Our explanatory variable of interest is the number of foreigners in the highly skilled portion of the labour force over total skilled employment, $D_S$. To identify top-skilled occupations we use the Standard Classification of Occupations (ISCO-88) of the International Labour Office (ILO, 1990). This classification takes into consideration the kind of work performed as well as the skill embodied in the work (Elias and McKnight, 2001). The occupations are thus grouped according to the similarity of the skills involved in the fulfilment of the tasks and duties of each job. 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 his or her job. For a description of the complete classification into the four skill groups, see Table A 1 in the online Appendix.

We define "skilled" workers as those workers occupied in the fourth skill group. The fourth skill level requires a college degree or equivalent period of relevant work experience and typically relates to professional occupations and managerial positions in corporate enterprises or national/local government,

[12] The OECD provides patent statistics which are computed on the basis of the fractional counting method by which for each patent a fraction equal to the share of a country's inventors over total inventors is assigned to each country. The use of count data models, which is common in the literature, is therefore not required.

[13] Both SCImago (2011) and OECD (2011) provide aggregate statistics by country.

such as legislators, senior officials and managers. A breakdown of the foreign population by skills reveals some differences among the various European countries (Table 1). Belgium, Hungary, Poland, Ireland and the UK have the highest share of highly skilled migrants (above 30%); Norway, Portugal, Finland, France, the Slovak Republic and the Netherlands follow (20-30%); finally Austria, Denmark, Spain, Germany, Italy Greece, the Czech Republic and Sweden are in the 10-20% range.[14]

The skills dimension embodied in our measure of diversity is not standard. Conventionally, the literature measures the skills level of foreign workers by using information on their educational attainment, independently of occupational considerations (Borjas, 2003; Card and Shleifer, 2009; Ottaviano and Peri, 2012). On the contrary, we use data on foreigners' occupations to capture more precisely their contribution to the creation of new knowledge. This distinction likely matters more for foreigners than for natives, as the literature shows that skill-mismatch often occurs among migrants (Green et al., 2007). Moreover, the skills classification described above takes into consideration the content of the educational capital embodied in different occupations, since 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). We therefore believe that our skills measurement is more precise. As a robustness check, however, we also show results using educational attainments as the basis for building our proxy for the share of skilled foreigners.

In

Figure 2, in addition to the top skills share of the foreign labour force (the last column of Table 1), we also show the contribution of foreigners to the skilled labour force as well as the contribution of the total number of foreigners to each country's population.[15] In France, Hungary, Ireland, Portugal and the UK, the share of skilled foreigners in skilled labour is more than proportional to the overall foreigner share. In Belgium, the Czech Republic, Finland and Norway the two shares are similar. All other European countries display a share of skilled foreigners lower than the overall foreigners' share, with some cases where the two shares are remarkably different (Austria, Germany and Greece).

The data used to compute this measure of diversity are taken from the EU Labour Force Survey (EU-LFS), which provides information on the nationalities of the respondents, along with their ISCO-88 occupation.[16]

A caveat of the EU-LFS is that it does not cover illegal migration. This limitation should however not be problematic in our context. The component of diversity that affects innovation is provided by highly skilled foreigners, who are most likely employed legally in highly skilled occupations. Highly qualified foreigners

[14] The data for Figure 2 are extracted from the 2000 round of censuses for all countries but Denmark, Finland, Norway and Sweden. For these last four countries, data are taken from population registers. For Iceland neither of the two sources is available.
[15] See note 14.
[16] For most of the countries, the EU-LFS provides information on both the nationality and the country of birth of non-nationals. In this paper we classify foreigners by nationality as this was the most comprehensive information. The EU-LFS has the great advantage of producing highly comparable data for the EU member states, as it is based on a common coding of questions, definitions and classifications of the variables.

illegally entering European countries eventually find low-skill jobs and should not influence the innovation potential of a country.

A second limitation of the dataset is that it does not allow constructing more sophisticated indexes of diversity, such as the Herfindahl Index. The EU-LFS classifies respondents only in two macro-categories, namely nationals or non-nationals. Details on the main areas of origin for migrants are available only for the last four waves (2004 onward), while detailed country information is never available. We cannot therefore compute a Herfindahl Index without drastically restricting the sample size. We however believe that this is only a minor limitation in our context. Since the share of nationals enters into the traditional computation of the Herfindahl Index, and since in European countries foreigners still account for a limited portion of the total population, a diversity measurement computed as the ratio of foreigners over the population and the Herfindahl index is highly correlated.[17] The same consideration holds true if we consider only the skilled portion of the foreign and total population.

Equation 2 also requires a proxy for the labour force working in the knowledge sector, $S$, which includes both foreigners and natives. An excellent candidate is the number of employees in technology and knowledge-intensive sectors, which provides information on the size of the research sector. We obtain this variable from the EUROSTAT database (EUROSTAT, 2011). This indicator also serves the purpose of capturing the size of a given economy, thus acting as a scaling factor since our dependent variables are not in per capita terms but in absolute values.

The availability of past knowledge that allows researchers to "stand on the shoulders of the giants" can be measured by cumulative functions of past innovation output. In the patent specification, we therefore use the rich information on past patenting output, which is available since the 1980s (OECD, 2011), as explained more in detail below. In the citation specification this approach is not possible, since data before 1996 are not available. Hence we resort to an input-based measure, using information on yearly total (public and private) intramural R&D expenditure, which we obtain from the EUROSTAT database (see for example Peri, 2005a).[18]

[17] The Herfindahl index, computed after 2004, and the ratio of foreigners to population displays a correlation of 0.99.

[18] The stock variable is constructed by applying the perpetual inventory method to each of the two measurements of innovative efforts as follows: $A_{i,t} = F_{i,t} + (1-\delta)A_{i,t-1}$ . The initial value of the stock is calculated as:$A_{i,t_0} = \frac{F_{i,t_0}}{\bar{g}+\delta}$ , where $F$ is the flow of either patents or R&D investment in a given year and country, $\delta$ =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 the flow of innovation efforts for the period between $t_0$ and $= 3$ , where $t_0$ is the first year of data availability (Bottazzi and Peri, 2003). This ensures that the choice of the initial value of the knowledge stock has the minimum possible impact on the subsequent levels of the variable. The patent stock is initialized in 1980. Data on GERD R&D expenditures are not available for all countries starting in the same year. We use the first year of data availability to build the initial knowledge stock variable, to limit the measurement error implicit in the rough estimation of the initial A. The base year is as follows: 1981 for Austria, Denmark, Finland, Germany, Greece, Iceland, Ireland, Italy, the Netherlands, Norway, Spain, Sweden and the United Kingdom, 1982 for Portugal, 1983 for Belgium, 1987 for Hungary and Poland, 1991 for France and 1993 for the Czech Republic and the Slovak Republic.

The country-fiixed effects in equation (4) capture country-specific financial and macroeconomic shocks and the potential heterogeneity of demand and immigration across country levels. Once these effects are checked through the introduction of fixed effects, the remaining variation of immigrants in a cell is assumed to be driven by supply shocks and the OLS estimates should be unbiased.

However, some lingering country-specific demand shocks are potentially in place, calling for an instrumental variable approach. 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, and especially skilled migrants, respond to economic opportunities in destination countries, a non-zero correlation exists between the economic outcomes and the share of (skilled) immigrants, biasing the estimated coefficient associated with such a share. A second source of bias exists due to measurement error in the share of (skilled) foreigners.

We use an instrumental variable approach to address both biases. Altonji and Card (1991) suggest an "ethnic enclave" instrument that has been largely used for migration shares in the subsequent empirical literature (Card and DiNardo, 2000; Card, 2001; Peri and Sparber, 2009; Ottaviano et al., 2013; D'Amuri and Peri, 2014; 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). To provide further exogeneity to the instrument, the imputed share is computed for the unskilled portion of migration. Unskilled immigrants provide cultural amenities that highly skilled foreigners find attractive, while they do not directly contribute to innovation. Specifically, we select the 1991 stock of unskilled migrants and predict the subsequent stock of low-educated migrants using total yearly immigration flows by area of origin from Ortega and Peri (2009). In agreement with D'Amuri and Peri (2014) we assume a 40 percent re-emigration rate to net the total gross inflows available. We calculate the imputed migrants' shares, $\widehat{D}$, as the ratio of the imputed stock of unskilled migrants to total imputed unskilled employment as follows:

$$\widehat{D}_{i,t} = \frac{F_{i,unskilled,1991} + \sum_N \frac{F^N_{i,unskilled,1991}}{F^N_{1991}} \Delta F^N_t}{\widehat{Empl}_{unskilled,i,t}}$$

where $F_{i,unskilled,1991}$ is the number of unskilled foreigners in country *i* in 1991; $F^N_{i,unskilled,1991}$ is the number of unskilled foreigners of area of origin *N* in country *i* in 1991.[19] $F^N_{1991}$ is the total number of foreigners from area of origin *N* in Europe in 1991; $\Delta F^N_t$ is the yearly immigration flows to Europe by area

[19] The areas of origin are: Central and South America, Eastern Europe, Middle east central Asia, North Africa, North America, Other Africa, South and Eastern Asia, Western Europe

of origin $N$ and $\widehat{Empl}_{unskilled,i,t}$ is the unskilled employment, defined as the stock of unskilled natives in each country in 1991, increased by the imputed stock of unskilled migrants in each country.[20]

The advantage of imputed shares is that they are determined only by the initial migration mix by origin and by the variation in flows across origin groups in the different European countries. Given the importance of ethnic networks, migrants tend to settle in established communities of similar origin. 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 with the economic situation after 1996. Moreover, the use of the unskilled share emphasizes the role of geography and taste, and minimizes the role of economic factors that might attract skilled workers.

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.

## 4. Discussion of Results

To account for possible serial correlation within countries, the standard errors in all our regressions are clustered at the country level. The small number of clusters in this application implies that an asymptotic refinement through bootstrapping should be implemented. Therefore, we use the wild cluster bootstrap procedure (Cameron et al., 2008; Davidson and MacKinnon, 2010). All tables report both the "plain" clustered p-values (in brackets) and wild cluster bootstrapped p-values for the coefficients of interest (in parenthesis).

### *4.1 Main Specification*

The results of the OLS regressions for both the patent and the citation specifications reported in

[20] Country-of-origin can be tightly linked to country of destination, and this argues against the validity of imputed shares as an instrument. In our case, the use of the unskilled portion of migration and yearly immigration flows to total Europe ($\Delta F_t^N$) should provide some confidence in the validity of the instrument. We also tried to exclude own-country flows from the European trend to be even more robust. Unfortunately, this alternative instrument is poorly correlated with the endogenous variable with an F-statistic extremely low.

Table 2, columns (1) and (3), indicate that the share of skilled migrants exerts a positive effect on both innovation measurements. Specifically, a one percent increase in the share of skilled migrants increases the number of patents by 0.08 percent and the number of citations by 0.15 percent, on average and *ceteribus paribus*.[21] All coefficients are significant at least at the 5 percent level, by using the both the clustered and the boostrapped standard errors. These results show that skilled foreign migrants in highly skilled occupations contribute both to the creation of general "public" knowledge and to the improvements of industrially applicable technologies.

The positive effect of foreign skilled labor on both innovation proxies is confirmed by the 2SLS estimates. The elasticities in the patent and citation equations are 0.89 and 0.63, respectively (columns 2 and 4), with significance level higher than 5 percent. In both specifications, these 2SLS point estimates are larger (i.e., more positive) that the corresponding OLS estimates.

A first explanation for this result is that the 2SLS addresses two sources of bias, moving in opposite directions. On the one hand, a potential measurement error in the statistics of skilled migrations should produce a negative bias in the estimated coefficient. As pointed out by Aydemir and Borjas (2011), the sampling error in the measurements of immigrant supply shift is responsible for a substantial reduction in the estimated impact of migration on wages.[22] On the other, the IV strategy controls for the effect of those unobservables governing both the location of foreigners in the different European countries as well as the evolution of patents or published documents. Economic theory traditionally suggests that the latter effect is responsible for an upward bias in the OLS coefficient, as migrants, and especially skilled migrants, respond positively to economic opportunities in destination countries. The increase in the elasticity from the OLS to the 2SLS would indicate that the downward bias due to the measurement error prevails in our case.

A second explanation for the larger coefficients of the 2SLS with respect to OLS coefficients is that the former estimates a local average treatment effect, LATE (Wooldridge, 2010). The instrumental variable coefficient hence reflects the effect on innovation of the skilled immigrants whose behavior is affected by the instrument. On the contrary, the OLS estimates the average treatment effect over the entire population. We recall that our instrument is computed by using information on unskilled enclaves and subsequent unskilled migration inflows, and its main rationale is that unskilled immigrants can provide amenities or cultural ties that channel high-skilled immigration. This instrument emphasizes the role of ethnic ties and taste over that of economic factors that might attract skilled workers specifically. Since the instrument captures the part of migration flows that follows ethnic networks, it may very well be that these immigrants are more productive

[21] Diversity may positively contribute to knowledge creation but with diminishing marginal returns. Too much 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 was introduced. The resulting coefficient was not statistically significant. This finding may indicate that the level of diversity in Europe is still too limited for detecting an inverted-U shape relationship.

[22] The authors find that allowing for such attenuation bias "can easily double, triple, and sometimes even quadruple the estimated wage impact of immigration".

as the network may have facilitated and optimized their entry into the labor market. Indeed, many other papers that use the ethnic enclave instruments in different settings find a similar result (among others, Card and DiNardo, 2000; Hunt et al., 2010; D'Amuri and Peri (2014); Bratti and Conti, 2014).

Also to be noted is the fact that our analysis results in a large difference in the size of the 2SLS and OLS coefficients. To check the robustness of these findings and explore if they are driven by specific countries, we carry out diagnostic tests on both the first stage and reduced form equations, as detailed in the online Appendix. This detective work identified observations and countries which have a great impact on the estimated coefficients (critical countries are Iceland, the Czech and Slovak Republics, and Portugal). After removing such influential observations, our 2SLS estimates are still higher than the OLS. However, the difference between the two shrinks marginally. Note that in a few cases it seems reasonable to assume that such influential observations emerge because of possible measurement error. Indeed, in the cases of Iceland and the Czech and Slovak Republics data for our key variables are extremely noisy. Portugal stands out potentially for a different reason: immigration trends reversed at the end of the 20$^{th}$ century, with Portugal becoming mainly an immigration destination for African Portuguese-speaking countries.

If we turn to the other controls, the coefficients of the variable measuring the stock of knowledge in a given country (stock of R&D expenditures) are in line with our expectations. A 1 percent increase in the knowledge stock is associated in the 2SLS specifications with a 0.6 percent and a 0.4 percent increase in patent applications and citations, respectively, with a level of significance of at least 5 percent The positive coefficients drive in favour of the "standing on shoulders" assumption: the accumulation of past knowledge benefits the creation of new knowledge. This is consistent with the R&D-based growth models of Romer (1990). The coefficient is however statistically smaller than one, indicating a weaker degree of intertemporal spillovers than that found in Abdih and Joutz (2006).

Conversely, a larger pool of skilled labour in not associated with a significant increase in the productivity of knowledge in our sample, since the estimated coefficients fail to reach acceptable levels of significance. One possible explanation is that the stock of knowledge already accounts in part for the researchers' population. The input-based measurement of R&D includes wages of researchers, while the output-based measurement embodies the overall productivity of the innovation sector, which depends on the pool of researchers. We test this hypothesis by running our main specifications without the stock of knowledge variable. The significance of the variable "total number of researchers" improved, but mostly in the OLS specification. One could argue that the productivity of researchers rather than their number is the main driver of innovation. In our case, this is better proxied by the stock of knowledge variable, which is either based on an output measurement (patent specifications) or accounts not only for the number of researchers, but also for the quality and money spent in labs, equipment and the like (citation specification).

The first stage estimates for the excluded instrument are reported in

Table A 2in the online Appendix, and show that the imputed shares have a positive and significant effect on the actual share of skilled migrants. The size of the F-tests indicates 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.

Our findings confirm the empirical results 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) as well as the empirical exercises on sub sets of European regions (Niebuhr, 2010 and Ozgen and al., 2011a). These studies document a positive contribution of the foreign skilled labour force to the production of patented knowledge. We also show that skilled foreigners contribute to the creation of more abstract public knowledge. Our results are consistent with the idea that foreign workers play a positive role by increasing the level of diversity, $D_s$, and they have a positive effect on the productivity of natives because new ideas are likely to arise through the interaction of diverse cultures and diverse approaches in problem solving. Not only do highly skilled immigrants display high rates of patenting, but they also allow natives to produce greater innovation (Hunt and Gauthier-Loiselle, 2010; Kerr and Lincoln, 2010).

We are aware that the share of skilled migrants, as computed here, does not provide any insight into the "type of diversity". The variety of ethnicities within foreigners, namely the country mix, is likely to be an important driver of economic development. Moreover, some ethnicities, given the language spoken, may better interact with nationals than others, thus providing greater complementarities. The proxy of diversity we constructed on EU-LFS data does not capture such aspects of diversity, since foreigners are only classified as non-nationals in the survey. One source of data that provides detailed bilateral information on origin and destination countries is the OECD International Migration database (OECD, 2013), available since 1990. The limitation of this dataset is that the skill breakdown of movers is not provided. Since our paper focuses on the determinants of knowledge formation, this is a major drawback. The distribution of skilled foreigners by country of origin in the different destinations may not be proportional to the distribution of total foreigners (

Figure 2). Skilled and unskilled foreigners may also follow different channels of entry, with the latter being more likely to exploit family ties.

The only reasonable approach, in our opinion, is to draw on the International Migration database to compute the Herfindahl index for the total migration population, excluding the share of nationals from the computation. This index is added in the estimation alongside the share of skilled foreigners, computed from the EU-LFS, to capture the variety and the distribution of the nationalities of foreigners. While the share of skilled foreigners captures the density of skilled migrants, the Herfindahl captures the diversity of the total pool of migrants, skilled and unskilled. In this way we offset the limits of a diversity measure which does not account for the variety of ethnicity in the foreign population.

Table 3, columns (1) to (4), reports the empirical findings of the model where the Herfindahl index is included as a regressor. While the density of skilled foreigners still exerts a positive effect on innovation (which is comparable to the estimates presented in

Table 2 and statistically significant at the 10 percent level for patents and 5 percent level for citations), the Herfindahl index, checking for the diversity of all migrants, is not significant. This is likely due to the limitations linked to the underlying data used in the construction of the index, namely the inclusion of both skilled and unskilled foreigners. For this reason, we only use the share of skilled foreigners as a measurement of diversity in the rest of the paper.

### *4.2 Occupation and education mismatch*

As argued above, our measurement of skilled foreigners based on occupation rather than education is unusual in the literature but, we believe, more appropriate for capturing the effective contribution of foreigners to the creation of knowledge. The distinction between the two methods of measuring skills with occupation and education is relevant particularly for foreigners, since higher education attainments do not guarantee that migrants are employed in highly skilled occupations. Nonetheless, we test the robustness of our results to the education-based skill metric traditionally used in the literature, since we believe that the comparison is beneficial in two ways. First, it helps in understanding if a mismatch in the allocation of skills in the labour market impacts the ability to innovate. Second, it serves to demonstrate whether the use of one measurement in place of the other can give rise to conflicting empirical findings.[23]

The correlation between the share of skilled migrants and the share of highly educated migrants is very high (0.90). In Figure 3, we plot the share of highly educated foreigners against the share of highly skilled foreigners, computed as a mean over the sample period in each country in our sample. Countries below the 45 degree line are those where there is a mismatch between educational attainments and employment among foreigners. In relative terms, Finland, the United Kingdom, Belgium, the Slovak Republic and Germany 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 countries such as Greece, Italy, Iceland, the Czech Republic, Portugal and Ireland. These countries display a disproportionally larger share of highly educated migrants as compared to highly skilled migrants, suggesting a relatively inefficient allocation of qualified migrants in the labour market. The high correlation of these two variables in Figure 3 suggest that mismatch is not as large a problem as expected. It should be noted that a large portion of mismatch is not really captured in this dataset on regular immigration, since over-education will disproportionally affect irregular immigrants.

[23] In EU-LFS information on the highest level of education completed is available, codified using the International Standard Classification of Education (ISCED). We define highly educated migrants as those with tertiary education, and compute the share with respect to the highly educated population in a given country.

Table 4 reports the results of the specification where we use the education-based classification of migrants. The empirical relationship between skilled migrants and innovation is robust to this alternative measure. The estimated coefficients of the 2SLS specifications are positive and statistically significant at the 5 percent level in both the patent and the citation specifications, though the asymptotic refinement makes the coefficient not statistically significant in the citation specification. In the patent specification, the elasticity of diversity computed along the skill dimension is statistically larger than the one computed for the education dimension. This is an interesting result, since it shows that traditional measures of diversity may underestimate the importance of foreigners in the innovation sector of destination countries.

The significant effect of both measurements of diversity suggests two main conclusions. First, regardless of where educated migrants are employed, they contribute to the creation of knowledge. The competence acquired through education generates positive externalities that spill over beyond the occupations they are employed in. Second, it indicates that the mismatch in qualification and occupation among migrants is relatively small. This is hardly surprising given the descriptive statistics presented in Figure 3.

## 5. Robustness Checks

The main specification presented above contains only a limited number of control variables, as derived from the theoretical setting. To avoid misspecification due to omitted variables bias we include some additional controls that may enter a knowledge production function. Throughout this section we refer to results that are reported in the Online Appendix.

First, we include a variable proxying for the expected global technology trends. This variable is constructed by calculating the distribution of patents and citations in different technologies/research areas in the base year.[24] The innovation in each technology/research field is then augmented for each period by using the technology/research specific worldwide growth rates. This variable allows us to check for expected innovation due to global trends and initial country allocations. The patent variables can be divided into nine technologies, based on the IPC classification provided in OECD (2011): Human Necessities; Performing Operations/Transport; Chemistry/Metallurgy; Textiles/Paper; Fixed Constructions; Mechanical Engineering/Lighting; Physics; Electricity. Conversely, bibliometric data is divided into four areas, based on the Scopus® Classification: Health, Life Sciences, Physical Sciences; Social Sciences. Results are presented in Table A 3 and show that the coefficients on the share of skilled foreigners and on the knowledge stock variable are robust to the inclusion of the expected technology trends in both the patent and the citation equation. Conversely, the coefficients of the trends themselves are insignificant.

Second, we include in our estimation a proxy of international knowledge spillovers. We assume that a preferential channel for knowledge flows across countries is represented by emigrants abroad. They are

[24] The base year is 1996 for the citation variable (first year of data availability) and 1991 for the patent variable (previous years are characterized by a non-ignorable number of zeros in some technological fields).

exposed to the foreign knowledge and at the same time they serve as a channel to their origin country. Kerr (2008), for example, documents that ethnic networks are important for knowledge diffusion from the US. For each country in our sample, we thus calculate the share of nationals in any other country in 1991 based on data from Docquier et al. (2009). We use these shares to weight the knowledge of each destination country. We sum over all destination countries and use this as a measurement of country specific foreign knowledge stock. The coefficients associated with this variable are significant in the patent specification, testifying that foreign knowledge positively contributes to the creation of domestic knowledge by allowing researchers to build on previous foreign innovations. Conversely, the variable fails to reach acceptable levels of significance in the citation specification. In both cases, the coefficients on the share of highly skilled migrants and on the own knowledge stock variable are robust.[25]

Third, another source of bias could emerge from geography-related shocks, which can be controlled for by regional-year fixed effects. The limited number of observations in our sample, however, does not allow us to introduce these variables. A potential problem here is that such geographical effects may influence the instrument, as long as the initial distribution of migrants by ethnicity is related to the spatial proximity of source and destination countries. This would adversely affect the validity of the instrumental variable approach. As a robustness check we formed expected migration shares by allocating yearly migration flows from each area of origin to the different destination countries according to a distance metric (rather than an ethnicity metric). In this distance metric the weights are higher for closer countries and smaller for countries farther away. These counterfactual shares are, by construction, subject to regional issues. A simple correlation test between the ethnic enclave instrument and the counterfactual share indicates that the two variables (ethnicity and distance-based imputed shares) are not correlated (-0.20). Far from being a definitive test, this still suggests that emigration flows that follow an ethnicity metric produce a different distribution of migrants as compared to counterfactual emigration flows that follow a distance metric. Hence, this supports the hypothesis that our original instrument is not subject to shocks that occurred between geographically close areas.

Fourth, we also check the robustness of our findings with respect to different proxies of general "public" knowledge. We use the number of documents published during a specific year and the number of citable documents (articles, reviews and conference papers) as dependent variables in place of the number of citations. The beneficial effect of diversity is robust to these changes, as shown in Table A 4. To check if lower income countries drive the result in the unweighted regressions, we use as weights GDP per capita at the beginning of the sample year. The choice of weights is determined by two factors. First, lower income countries may display sudden changes in innovation and in the share of skilled foreigners as they eventually catch up. Second, lower income countries have a smaller pool of migrants and/or might be inherently less

[25] Two additional controls have been added in the basic specification and are available from the authors upon request. First, in line with Niebuhr (2010), we included a measurement of the industrial structure of the countries, computed as the ratio between the manufacturing and the service value added. Second, we also added a control for the size of the country, namely population. Both have a non-significant impact on innovation.

efficient in collecting data on migration flows. This would imply that their statistics are more affected by measurement error. The weighted regression on the contrary gives larger weights to richer countries, which have a larger pool of foreigners, more reliable migration statistics and where innovation has traditionally been in place. The estimated coefficients presented in Table A 5 are robust to the application of the weights.

Fifth, the theoretical setting suggests that the knowledge production function depends on the labour force in the research sector. Therefore, the diversity variable in this paper is measured by selecting only the skilled portion of the foreign population. However, immigration may boost innovation through indirect channels, such as by lowering the cost of domestic services and therefore by increasing the labour supply of domestic workers, such as native women (Cortes and Tessada, 2011; Barone and Mocetti, 2011; Farre et al., 2011) or by increasing the productivity of native workers, who can select tasks and occupations where they can exploit a comparative advantage (Cattaneo et al., 2013; D'Amuri and Peri, 2014; Peri and Sparber, 2009, 2011). This implied that, not only high-skilled but also foreigners with lower skills can indirectly contribute to innovation. To check whether this is indeed the case, we replace the measure of skilled share by a measure of unskilled share, computed by using information on foreigners employed in the first skill group. Table A 6 reports the empirical findings. The coefficient of the share of low-skilled foreigners is statistically significant both in the patent and in the citation specifications. This finding however could be due to an omitted variable bias, as the share of unskilled migrants can proxy for the share of skilled ones. We therefore add the two shares jointly in the specification. While the coefficients of skilled migrants are robust to the inclusion of the unskilled counterpart, the coefficients of the unskilled migrants are now not statistically significant.[26] These findings do not contradict the existing literature, which finds an indirect effect of migration on economic outcomes. While this effect is positive and strong for general economic outcomes, if we limit our attention to innovation outcomes, as in the present case, the direct effect largely prevails over the indirect one.

Sixth, in the specifications presented so far we assumed a limited delay in the response of the dependent variable to changes in the explanatory variables. As an additional check, we have verified the robustness of our findings to the assumption of a slower response of the dependent variable. We rerun the main specification by using two to four years lag in the controls. The coefficients of the diversity variable and of the stock of knowledge are robust to these different assumptions. In the online Appendix, Table A 7and

[26] We cannot check the robustness of this result in an IV setting because the presence of two endogenous variables (diversity proxies) and of one instrumental variable (imputed shares) makes the model under-identified.

Table A 8 report the estimated coefficients.

Finally, in the online Appendix we also present the results of the base regression for different technology subfields, both for patents and citations (Table A 9and

Table A 10). There is some evidence that the effect of migration might be different by sectors, especially in the case of citations. The differential impact of diversity could be attributed to two main reasons. First, the distribution of migrants across sectors in the receiving countries might not be homogenous. As a result, the sectors whose estimated coefficient is positive might be the ones where most of the skilled migrants are employed. Second, knowledge production in a given sector might inherently be associated with higher returns, due for example to higher productivity. Given the aggregate nature of our proxy of diversity, which is not available at the sectoral level but only at the country level, we cannot clearly distinguish between these two effects in the present case.

## 6. Conclusion

In this paper we propose a simple knowledge production function in which innovation is a function of the stock of knowledge, the number of people employed in the research sector and the share of highly-skilled foreigners. We provide two proxies for the innovative capacity of countries, namely the number of PCT patent applications and the number of citations to published articles. Both are widely adopted measurements, the first capturing private, patentable and applied knowledge, the second being a better indicator of general (public) knowledge in a society. In the sample of 20 European countries considered in this study, the two measurements are highly correlated.

We show that highly-skilled foreigners have a positive impact on the innovative capacity of the recipient countries both for industrially applicable innovations and for more general abstract knowledge. This evidence extends existing results to a broader set of countries than previously analysed and to the use of alternative proxies for innovation. We reinforce the idea that complementarities exist between natives and foreigners. As in the micro-analyses on this topic, we find a positive synergic interaction of diverse cultures and diverse approaches in problem solving. Skilled migrants employed in highly skilled jobs positively impact on innovation by increasing researchers' average productivity. The results we present hold true in a series of robustness checks, such as the inclusion of additional control variables, the use of longer lags, the use of different proxies for key explanatory variables, and the exclusion of certain countries from the sample.

In this analysis we employ an unconventional skills measurement to account for skilled migrants. Rather than measuring education skills, we build our diversity index by using information on the actual occupation of foreign workers. Indeed, one would expect the actual employment of skills to determine an effect on innovation. As a robustness check, we also test whether the effect of highly-skilled migrants is robust to the use of the more traditional proxy based on education data. We find that the elasticities of diversity computed according to the two alternative skill measurements are highly comparable in the case of public knowledge (citations). On the contrary, the education-based measurement tends to slightly underestimate the contribution of skilled foreigners to the creation of industrially applicable knowledge (patents). Moreover, our estimates are robust to the inclusion of global technology trends, spillovers, geography-related shocks, and to different assumptions regarding the length on the innovation process.

Our results thus shed light on and complement the current debate on the creation of a common EU migration policy framework and the fostering of highly-skilled migration to Europe. We show that indeed the belief that European competitiveness can benefit from attracting highly-skilled migration is founded. An effective allocation of labour resources that reduce the over-qualification of migrants is a pre-condition for reaping higher benefits associated with highly-skilled migration flows. As a result, reforming the system to ease the access and recruitment of highly qualified migration would most likely be associated with significant short-term benefits in the creation of knowledge. In light of these results, schemes such as the EU Blue Card appear as a positive first step in the direction of fostering European innovativeness and competitiveness.

The empirical findings also confirm that the stock of existing knowledge has a positive effect on innovation. This supports the "standing on shoulders" assumption, to the extent that the accumulation of past knowledge increases the creation of new knowledge. Our results suggest that in order to make the EU competitive in the innovation domain, recruitment of highly-skilled migrants is only one of the key ingredients. Investments in R&D are at least as important, and this raises concern over the recent discussion about implementing research budget cuts in both member states and the EU.

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**Appendix A. Supplementary data**

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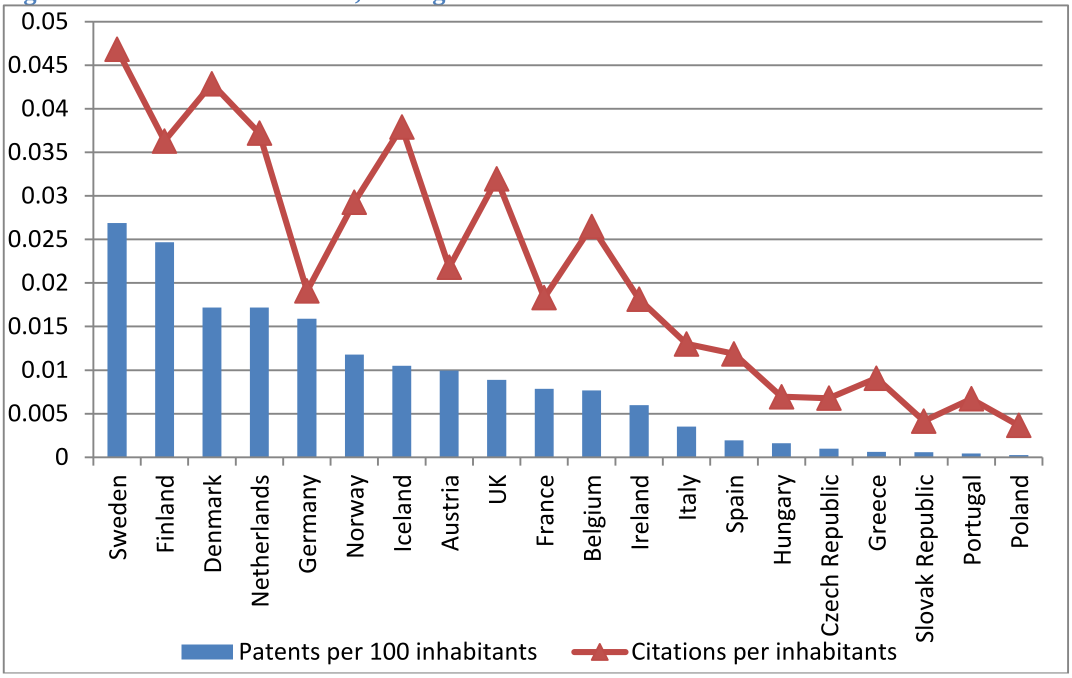
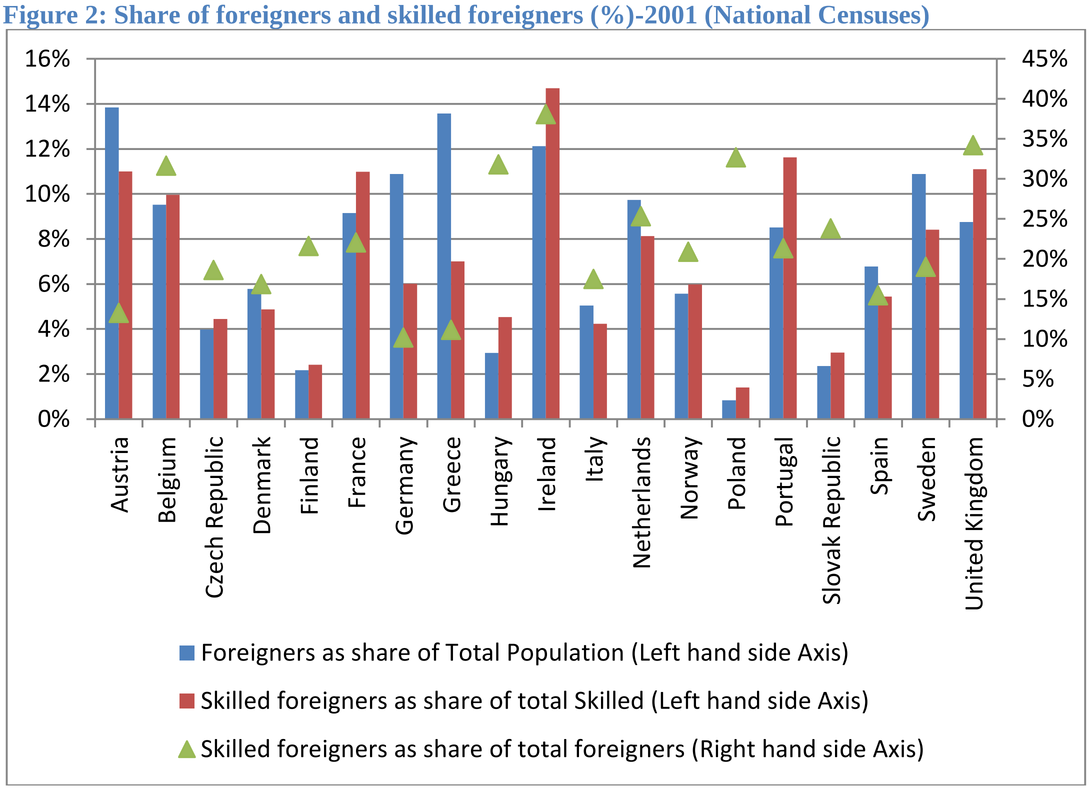
## Figures and Tables

Figure 1: Patents and Citations, average 1995-2008



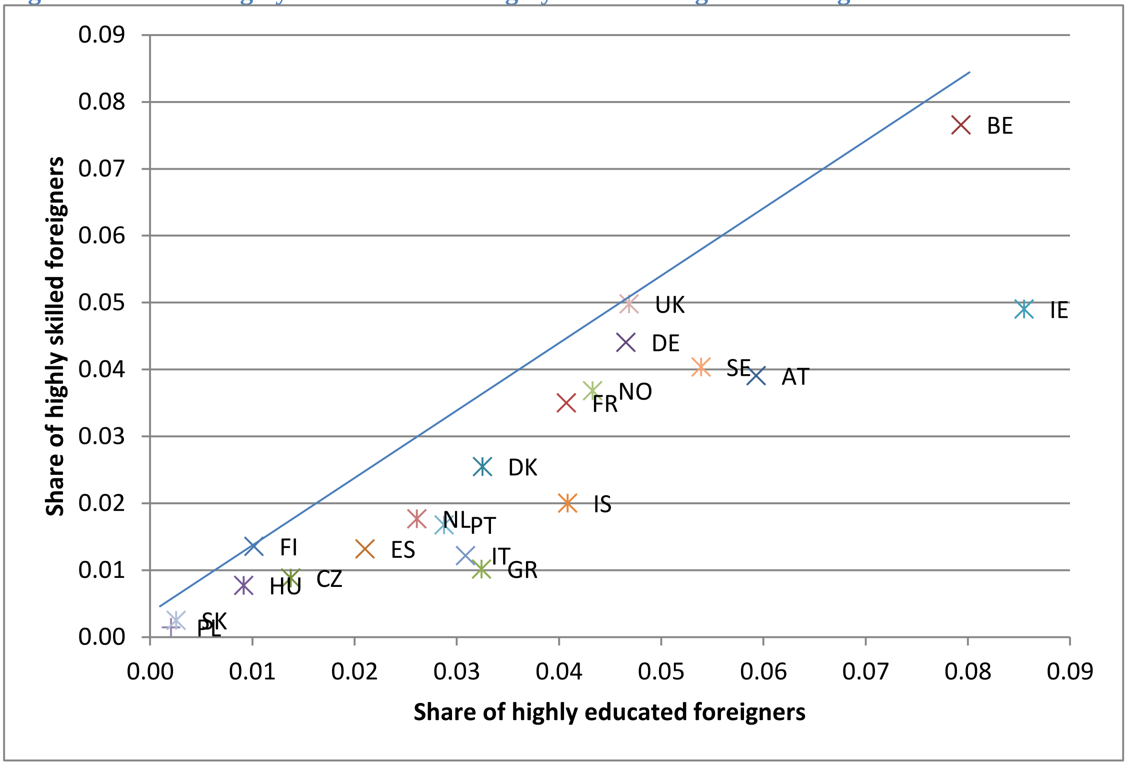

Source: OECD Patent Statistics Database (OECD, 2011) and SCImago Journal & Country Rank (SCImago, 2011)

Figure 2: Share of foreigners and skilled foreigners (%)-2001 (National Censuses)




Note: The data for Figure 2 are extracted from the 2000 round of censuses for all countries but Denmark, Finland, Norway and Sweden. For these last four countries, data are taken from population registers. For Iceland neither of the two sources is available, hence it is missing from the Figure. Skilled foreigners are those occupied as technicians and associate professionals, legislators, senior officials, managers and professionals, according to the Standard Classification of Occupations (ISCO-88).

**Figure 3: Share of highly educated versus highly skilled foreigners- average 1996-2008.**




Source: EU Labour Force Survey (EU-LFS)

**Table 1 Distribution of foreign workers into skill groups (%)-2001**

| | Skill1 | Skill2 | Skill3 | Skill4 |
|---|---|---|---|---|
| Austria | 28.2 | 46.2 | 12.4 | 13.3 |
| Belgium | 12.3 | 47.2 | 8.9 | 31.6 |
| Czech Republic | 11.8 | 51.9 | 17.7 | 18.6 |
| Denmark | 22.6 | 46.3 | 14.2 | 16.9 |
| Finland | 14.5 | 49.6 | 14.3 | 21.6 |
| France | 11.0 | 52.9 | 14.1 | 22.1 |
| Germany | 20.0 | 56.6 | 13.3 | 10.2 |
| Greece | 30.3 | 54.3 | 4.3 | 11.2 |
| Hungary | 5.8 | 48.5 | 13.9 | 31.8 |
| Ireland | 6.8 | 46.3 | 8.8 | 38.1 |
| Italy | 22.5 | 46.2 | 13.8 | 17.5 |
| Netherlands | 14.2 | 44.9 | 15.6 | 25.3 |
| Norway | 11.8 | 48.4 | 18.9 | 20.9 |
| Poland | 7.0 | 48.0 | 12.3 | 32.7 |
| Portugal | 14.9 | 50.9 | 12.8 | 21.3 |
| Slovak Republic | 11.4 | 45.4 | 19.3 | 23.8 |
| Spain | 27.4 | 49.4 | 7.8 | 15.5 |
| Sweden | 13.3 | 54.7 | 13.0 | 19.0 |
| United Kingdom | 10.4 | 42.3 | 13.1 | 34.2 |

Source: data are taken from 2000 round of censuses. Only for Denmark, Finland, Norway and Sweden are data taken from population registers.

**Table 2: The effect of skilled foreigners on innovation –OLS and 2SLS**

| | Patents | | Citations | |
|---|---|---|---|---|
| | OLS | 2SLS | OLS | 2SLS |
| | (1) | (2) | (3) | (4) |
| $\ln(D_s)$ | 0.0766 | 0.894 | 0.145 | 0.631 |
| | [0.0276] | [0.0258] | [0.00279] | [0.00157] |
| | (0.0378) | (0.0364) | (0.0096) | (0.0388) |
| ln(A) | 0.756 | 0.557 | 0.451 | 0.445 |
| | [0.0259] | [0.0105] | [0.0440] | [0.000282] |
| | (0.0044) | (0.05099) | (0.0406) | (0.05079) |
| ln(S) | -0.0923 | -0.0256 | 0.195 | 0.155 |
| | [0.747] | [0.934] | [0.284] | [0.499] |
| | (0.84232) | (0.94011) | (0.33017) | (0.57434) |
| Observations | 213 | 213 | 213 | 213 |
| R-squared | 0.786 | 0.481 | 0.781 | 0.438 |
| Number of countries | 20 | 20 | 20 | 20 |
| F-test 1st stage (standard) | | 18.64 | | 23.26 |
| F-test 1st stage (bootstrap) | | 9.56 | | 11.02 |

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) it is the natural logarithm of the number of citations to publications in year t. Country dummies and year dummies are included in all specifications. Clustered p-values are reported in brackets. Wild cluster bootstrapped p-values are reported in parentheses and are performed on 10,000 replications. The excluded instrument in the first stage of the 2SLS is the log of imputed shares.

**Table 3: The effect of diversity on innovation, Herfindahl Index**

| | Patents | | Citations | |
|---|---|---|---|---|
| | OLS | 2SLS | OLS | 2SLS |
| | (1) | (2) | (3) | (4) |
| $\ln(D_s)$ | 0.053 | 0.734 | 0.127 | 0.670 |
| | [0.220] | [0.0598] | [0.0108] | [0.0171] |
| | (0.29977) | (0.06859) | (0.0274) | (0.05379) |
| Ln(Herfindahl) | 0.054 | -0.840 | 0.263 | -0.617 |
| | [0.877] | [0.410] | [0.457] | [0.439] |
| | (0.87251) | (0.56854) | (0.50995) | (0.48195) |
| ln(A) | 0.959 | 0.671 | 0.452 | 0.286 |
| | [0.00123] | [0.00981] | [0.0853] | [0.180] |
| ln(S) | -0.162 | -0.022 | 0.185 | 0.193 |
| | [0.411] | [0.928] | [0.295] | [0.389] |
| Observations | 183 | 182 | 183 | 182 |
| R-squared | 0.825 | 0.629 | 0.801 | 0.442 |
| Number of countries | 18 | 17 | 18 | 17 |
| F-test 1st stage | | 12.8 | | 9.555 |

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) it is the natural logarithm of the number of citations to publications in year t. Country dummies and year dummies are included in all specifications. Clustered p-values are reported in brackets. Wild cluster bootstrapped p-values are reported in parentheses and are performed on 10,000 replications. The excluded instrument in the first stage of the 2SLS is the log of imputed shares.

**Table 4: The effect of skilled foreigners on innovation: Alternative skill measurement- education attainment**

| | Patents | | Citations | |
|---|---|---|---|---|
| | OLS | 2SLS | OLS | 2SLS |
| | (1) | (2) | (3) | (4) |
| $\ln(D_{s\ education})$ | 0.0967 | 0.649 | 0.0522 | 0.634 |
| | [0.131] | [0.00405] | [0.266] | [0.0187] |
| | (0.14319) | (0.0334) | (0.26317) | (0.11779) |
| ln(A) | 1.006 | 0.810 | 0.469 | 0.282 |
| | [0.000203] | [9.16e-05] | [0.105] | [0.265] |
| ln(S) | -0.199 | -0.518 | 0.203 | -0.213 |
| | [0.327] | [0.0588] | [0.361] | [0.538] |
| Observations | 207 | 207 | 207 | 207 |
| R-squared | 0.805 | 0.66 | 0.759 | 0.286 |
| Number of countries | 20 | 20 | 20 | 20 |
| F-test 1st stage | | 20.31 | | 27.51 |

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) it is the natural logarithm of the number of citations to publications in year t. Country dummies and year dummies are included in all specifications. Clustered p-values are reported in brackets. Wild cluster bootstrapped p-values are reported in parentheses and are performed on 10,000 replications. The excluded instrument in the first stage of the 2SLS is the log of imputed shares.

## On line Appendix

### Table A 1: Definitions of the four ISCO skill levels

| Skill Level | ISCO Occupation | Description |
|---|---|---|
| First | 9. Elementary occupations | They require the performance of simple, 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;<br>5. Service workers and shop and market sales workers;<br>6. Skilled agricultural and fishery workers;<br>7. Craft and related trades workers;<br>8. Plant and machine operators and assemblers | They involve the performance of tasks such as operating machinery and electronics 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 arithmetic 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 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 formal |

| | | |
|---|---|---|
| | | education. |
| Fourth | 1. Legislators, senior officials and managers;<br>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 for extending 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 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 A 2: First Stage for the excluded instrument of the share of highly-skilled migrants**

| VARIABLES | Patents (1) | Citation (2) |
|---|---|---|
| ln(A) | 0.105 | -0.119 |
| | [0.492] | [0.287] |
| ln(S) | -0.383 | -0.314 |
| | [0.221] | [0.283] |
| ln(Imputed Share) | 2.607 | 2.814 |
| | [0.000381] | [0.000122] |
| | 0.003 | 0.0018 |
| Observations | 213 | 213 |
| R-squared | 0.341 | 0.341 |
| Number of countries | 20 | 20 |
| F( 1, 19) = (standard) | 18.64 | 23.26 |
| F( 1, 19) = (bootstrap) | 9.56 | 11.02 |

Notes: Country dummies and year dummies are included. Clustered p-values are reported in brackets. Wild cluster bootstrapped p-values are reported in parentheses and are performed on 10,000 replications.

**Table A 3: The effect of skilled foreigners on innovation: Additional control variables**

| | Patents | | | | Citations | | | |
|---|---|---|---|---|---|---|---|---|
| | OLS | 2SLS | OLS | 2SLS | OLS | 2SLS | OLS | 2SLS |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $\ln(D_s)$ | 0.0889 | 1.109 | 0.0902 | 1.126 | 0.124 | 0.636 | 0.127 | 0.742 |
| | [0.0765] | [0.0210] | [0.0315] | [0.00873] | [0.00214] | [0.00720] | [0.00183] | [0.00190] |
| | (0.09499) | (0.0428) | (0.0358) | (0.0226) | (0.006) | (0.05099) | (0.0038) | (0.021) |
| ln(A) | 0.734 | 0.459 | 0.669 | 0.387 | 0.395 | 0.409 | 0.401 | 0.422 |
| | [0.0345] | [0.0216] | [0.0270] | [0.0160] | [0.0817] | [0.00529] | [0.0860] | [0.00316] |
| ln(S) | -0.0499 | 0.22 | 0.0439 | 0.32 | 0.267 | 0.143 | 0.251 | 0.091 |
| | [0.860] | [0.541] | [0.854] | [0.407] | [0.124] | [0.564] | [0.177] | [0.742] |
| ln(Knowledge Spillovers) | | | 6.888 | 7.055 | | | -4.088 | -7.113 |
| | | | [0.0763] | [0.000866] | | | [0.350] | [0.194] |
| | | | (0.13579) | (0.10179) | | | (0.39296) | (0.26957) |
| ln(World Trend) | -1.127 | -0.0537 | -0.782 | 0.315 | -0.0493 | -0.00523 | -0.00394 | 0.0824 |
| | [0.170] | [0.960] | [0.298] | [0.784] | [0.640] | [0.952] | [0.972] | [0.419] |
| | (0.24658) | (0.9585) | (0.37396) | (0.81992) | (0.67493) | (0.9569) | (0.9725) | (0.44596) |
| Observations | 203 | 203 | 203 | 203 | 203 | 203 | 203 | 203 |
| R-squared | 0.801 | 0.517 | 0.816 | 0.524 | 0.786 | 0.398 | 0.789 | 0.231 |
| Number of countries | 19 | 19 | 19 | 19 | 20 | 20 | 20 | 20 |
| F-test 1st stage | | 16.96 | | 16.73 | | 14.41 | | 14.99 |

Notes: In columns (1) through (4) the dependent variable is the natural logarithm of the patent applications filed under the PCT recorded by priority date; in columns (5) through (8) it is the natural logarithm of the number of citations to publications in year t. Country dummies and year dummies are included in all specifications. Clustered p-values are reported in brackets. Wild cluster bootstrapped p-values are reported in parentheses and are performed on 10,000 replications. The excluded instrument in the first stage of the 2SLS is the log of imputed shares.

**Table A 4: The effect of skilled foreigners on innovation, alternative measurements of general knowledge**

| | Published Documents | | Citable Documents | |
|---|---|---|---|---|
| | OLS | 2SLS | OLS | 2SLS |
| | (1) | (2) | (3) | (4) |
| $\ln(D_s)$ | 0.0752 | 0.441 | 0.0818 | 0.450 |
| | [0.0612] | [0.00565] | [0.0478] | [0.00529] |
| | (0.0442) | (0.025) | (0.0382) | (0.0288) |
| ln(A) | 0.477 | 0.472 | 0.478 | 0.474 |
| | [0.00264] | [1.61e-07] | [0.00297] | [1.12e-07] |
| ln(S) | 0.119 | 0.0885 | 0.107 | 0.0769 |
| | [0.317] | [0.597] | [0.369] | [0.649] |
| Observations | 213 | 213 | 213 | 213 |
| R-squared | 0.925 | 0.803 | 0.919 | 0.791 |
| Number of countries | 20 | 20 | 20 | 20 |
| F-test 1st stage | | 23.26 | | 23.26 |

Notes: In columns (1) and (2) the dependent variable is the natural logarithm of the published documents; in columns (3) and (4) it is the natural logarithm of the number of citable documents. Country dummies and year dummies are included in all specifications. Clustered p-values are reported in brackets. Wild cluster bootstrapped p-values are reported in parentheses and are performed on 10,000 replications. The excluded instrument in the first stage of the 2SLS is the log of imputed shares.

**Table A 5: The effect of skilled foreigners on innovation. Weighted regressions**

| | Patents | | Citations | |
|---|---|---|---|---|
| | OLS | 2SLS | OLS | 2SLS |
| | (1) | (2) | (3) | (4) |
| $\ln(D_s)$ | 0.0954 | 0.897 | 0.150 | 0.541 |
| | [0.0340] | [0.0207] | [0.00286] | [0.0123] |
| | (0.0466) | (0.0392) | (0.017) | (0.0492) |
| ln(A) | 0.674 | 0.499 | 0.466 | 0.420 |
| | [0.0341] | [0.0103] | [0.0141] | [0.000209] |
| ln(S) | -0.0518 | 0.0316 | 0.187 | 0.173 |
| | [0.858] | [0.902] | [0.234] | [0.409] |
| Observations | 213 | 213 | 213 | 213 |
| R-squared | 0.792 | 0.547 | 0.820 | 0.652 |
| Number of countries | 20 | 20 | 20 | 20 |
| First st. F-stat | | 18.80 | | 20.93 |

Notes: The regressions are weighted by GDP per capita at the beginning of the sample year. 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) it is the natural logarithm of the number of citations to publications in year t. Country dummies and year dummies are included in all specifications. Clustered p-values are reported in brackets. Wild cluster bootstrapped p-values are reported in parentheses and are performed on 10,000 replications. The excluded instrument in the first stage of the 2SLS is the log of imputed shares.

**Table A 6: The effect of low-skilled foreigners on innovation**

| | Patents | | | Citations | | |
|---|---|---|---|---|---|---|
| | OLS | 2SLS | OLS | OLS | 2SLS | OLS |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\ln(D_{s\_4})$ | | | 0.0709 | | | 0.135 |
| | | | [0.0257] | | | [0.000221] |
| | | | (0.05) | | | (0.0094) |
| $\ln(D_{s\_1})$ | 0.0464 | 0.534 | 0.0336 | 0.0770 | 0.428 | 0.0444 |
| | [0.394] | [0.0254] | [0.539] | [0.0843] | [0.0177] | [0.238] |
| | (0.43596) | (0.0288) | (0.55954) | (0.12159) | (0.0438) | (0.31217) |
| ln(A) | 0.732 | 0.313 | 0.725 | 0.390 | -0.0203 | 0.437 |
| | [0.0388] | [0.348] | [0.0379] | [0.0873] | [0.951] | [0.0323] |
| ln(S) | -0.136 | -0.596 | -0.116 | 0.109 | -0.347 | 0.141 |
| | [0.615] | [0.0563] | [0.664] | [0.633] | [0.252] | [0.494] |
| Observations | 212 | 212 | 212 | 212 | 212 | 212 |
| R-squared | 0.728 | 0.578 | 0.785 | 0.768 | 0.452 | 0.791 |
| Number of countries | 20 | 20 | 20 | 20 | 20 | 20 |
| First st. F-stat | | 9.433 | | | 10.94 | |

Notes: In columns (1) to (3) the dependent variable is the natural logarithm of the patent applications filed under the PCT recorded by priority date; in columns (4) to (6) it is the natural logarithm of the number of citations to publications in year t. Country dummies and year dummies are included in all specifications. Clustered p-values are reported in brackets. Wild cluster bootstrapped p-values are reported in parentheses and are performed on 10,000 replications. The excluded instrument in the first stage of the 2SLS is the log of imputed shares.

**Table A 7: The effect of skilled foreigners on innovation, two-to-four-year lag. Patents**

| | Two-year lags | | Three-year lags | | Four-year lags | |
|---|---|---|---|---|---|---|
| | OLS | 2SLS | OLS | 2SLS | OLS | 2SLS |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\ln(D_s)$ | 0.0852 | 1.139 | 0.121 | 1.262 | 0.0985 | 1.233 |
| | [0.209] | [0.0346] | [0.283] | [0.00974] | [0.131] | [0.0134] |
| | (0.24358) | (0.05199) | (0.41376) | (0.0196) | (0.18598) | (0.05079) |
| ln(A) | 0.666 | 0.436 | 0.457 | 0.279 | 0.29 | 0.203 |
| | [0.134] | [0.129] | [0.258] | [0.262] | [0.451] | [0.383] |
| ln(S) | -0.323 | -0.0788 | -0.422 | -0.029 | -0.38 | 0.172 |
| | [0.488] | [0.831] | [0.336] | [0.935] | [0.415] | [0.580] |
| Observations | 194 | 194 | 174 | 174 | 154 | 154 |
| R-squared | 0.711 | 0.124 | 0.654 | -0.322 | 0.58 | -0.716 |
| Number of countries | 20 | 20 | 19 | 19 | 18 | 18 |
| F-test 1st stage | | 20.12 | | 20.54 | | 14.32 |

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. Clustered p-values are reported in brackets. Wild cluster bootstrapped p-values are reported in parentheses and are performed on 10,000 replications. The excluded instrument in the first stage of the 2SLS is the log of imputed shares.

**Table A 8: The effect of skilled foreigners on innovation, two-to-four-year lag. Citations**

| | Two-year lags | | Three-year lags | | Four-year lags | |
|---|---|---|---|---|---|---|
| | OLS | 2SLS | OLS | 2SLS | OLS | 2SLS |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\ln(D_s)$ | 0.111 | 0.648 | 0.0979 | 0.662 | -0.00211 | 0.64 |
| | [0.00738] | [0.00335] | [0.0169] | [0.00405] | [0.969] | [0.0363] |
| | (0.015) | (0.0466) | (0.0188) | (0.0304) | (0.9811) | (0.04) |
| ln(A) | 0.417 | 0.349 | 0.434 | 0.342 | 0.463 | 0.315 |
| | [0.0875] | [0.0153] | [0.0573] | [0.0390] | [0.0354] | [0.219] |
| ln(S) | 0.16 | 0.222 | 0.0278 | 0.186 | -0.033 | 0.281 |
| | [0.378] | [0.368] | [0.854] | [0.347] | [0.851] | [0.238] |
| Observations | 194 | 194 | 174 | 174 | 154 | 154 |
| R-squared | 0.772 | 0.349 | 0.796 | 0.324 | 0.815 | 0.183 |
| Number of countries | 20 | 20 | 19 | 19 | 18 | 18 |
| F-test 1st stage | | 21.18 | | 19.15 | | 10.24 |

Notes: The dependent variable is the natural logarithm of the number of citations to publications in year t. Country dummies and year dummies are included in all specifications. Clustered p-values are reported in brackets. Wild cluster bootstrapped p-values are reported in parentheses and are performed on 10,000 replications. The excluded instrument in the first stage of the 2SLS is the log of imputed shares.

**Table A 9: The effect of skilled foreigners on innovation. Patents by technology fields**

| | Biotechnology | | ICT | | Human Necessities | | Transport | | Chemistry | | Textiles | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | OLS | 2SLS | OLS | 2SLS | OLS | 2SLS | OLS | 2SLS | OLS | 2SLS | OLS | 2SLS |
| $\ln(D_s)$ | -0.07 | 0.69 | 0.05 | 1.784 | 0.07 | 0.42 | 0.157 | 0.38 | -0.04 | 0.605 | 0.05 | 0.25 |
| | [0.610] | [0.451] | [0.610] | [0.0225] | [0.308] | [0.321] | [0.0816] | [0.340] | [0.674] | [0.0935] | [0.788] | [0.636] |
| | (0.80) | (0.60) | (0.60) | (0.04) | (0.30) | (0.50) | (0.30) | (0.50) | (0.90) | (0.20) | (0.80) | (0.70) |
| | | {1} | | {0.2475} | | {1} | | {1} | | {0.6545} | | {0.636} |

| | Fixed Constructions | | Mechanical Engineering | | Physics | | Electricity | | Medical | | Pharmaceuticals | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | OLS | 2SLS | OLS | 2SLS | OLS | 2SLS | OLS | 2SLS | OLS | 2SLS | OLS | 2SLS |
| $\ln(D_s)$ | 0.21 | 1.288 | 0.04 | 0.99 | 0.09 | 1.207 | 0.14 | 2.352 | -0.11 | 0.19 | 0.06 | 1.122 |
| | [0.236] | [0.0519] | [0.605] | [0.168] | [0.145] | [0.0491] | [0.346] | [0.0188] | [0.437] | [0.476] | [0.642] | [0.0654] |
| | (0.20) | (0.10) | (0.60) | (0.30) | (0.10) | (0.10) | (0.40) | (0.04) | (0.50) | (0.50) | (0.60) | (0.20) |
| | | {0.4671} | | {1} | | {0.491} | | {0.2256} | | {0.952} | | {0.5232} |

Notes: The dependent variable is the natural logarithm of the patent applications filed under the PCT recorded by priority date in the different fields. Country dummies and year dummies are included in all specifications. Clustered p-values are reported in brackets. Wild cluster bootstrapped p-values are reported in parentheses and are performed on 10,000 replications. The Holm-Bonferroni p-values corrected for multiple comparisons are reported in curly brackets. The excluded instrument in the first stage of the 2SLS is the log of imputed shares.

**Table A 10: The effect of skilled foreigners on innovation. Citations by technology fields**

| | Health | | Life Sciences | | Physical Sciences | | Social Sciences | |
|---|---|---|---|---|---|---|---|---|
| | OLS | 2SLS | OLS | 2SLS | OLS | 2SLS | OLS | 2SLS |
| ln($D_s$) | 0.149** | 0.927*** | 0.157*** | 0.713*** | 0.147*** | 0.489** | 0.180*** | 0.770*** |
| | [0.0115] | [0.000799] | [0.00165] | [0.000502] | [0.00830] | [0.0155] | [9.80e-05] | [0.000294] |
| | (0.01) | (0.05) | 0.02 | (0.04) | 0.01 | (0.08) | (0.01) | (0.03) |
| | | {0.001598} | | {0.001506} | | {0.0155} | | {0.001176} |

Notes: The dependent variable is the natural logarithm of the number of citations to publications in year t in the different fields. Country dummies and year dummies are included in all specifications. Clustered p-values are reported in brackets. Wild cluster bootstrapped p-values are reported in parentheses and are performed on 10,000 replications. The Holm-Bonferroni p-values corrected for multiple comparisons are reported in curly brackets. The excluded instrument in the first stage of the 2SLS is the log of imputed shares.