Immigration, Population Diversity and Innovation of Italian regions*

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Abstract

We use very small geographical units (NUTS - Eurostat Nomenclature of territorial units for statistics - 3 level, i.e. provinces) to investigate the causal effect of foreign immigration on innovation (patents' applications). Using instrumental variables' estimation (and instruments based on immigrant *enclaves*), we find that the overall stock of immigrants has a significant negative effect on innovation of Italian provinces: rising the share of immigrants by one percent point (p.p.) decreases patenting by 0.064 percent. However, distinguishing the effect between low and high-skilled migrants shows that the aggregate negative effect is driven by the prevalence in Italy of low-educated immigrants. In fact, our estimates suggest that an increase of 1 p.p. in the share of low skilled foreign migrants on the population induces a reduction in patents' applications per 1000 inhabitants in a range between 0.094 and 0.186 percent, according to the method used to classify immigrants by skill level. Instead, presumably due to the extremely low presence of high skilled immigrants in Italy and to the underutilization of their competencies, the impact of high skilled immigrants on innovation is positive, but cannot be precisely estimated.

JEL classification. O3 · J2
Keywords. Innovation · Immigration · Regions

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1 Introduction

At the turn of the century, 4.6% of world population was born in a different country from the one where it currently lived. In the OECD countries this share rises to 8.9%. 31.4 million of immigrants were living in the U.S.; 7.8 million in Germany; 5.6 million in France; 5.3 million in Canada; 2 million in Italy. Several non-OECD countries also had very large foreign-born populations. 11 million live in Russia; 6 million in India; 1.8 million in Israel. In relative terms, high shares of immigrants were recorded in several OECD countries in 2000 (in Luxembourg 37% of the population was foreign-born; in Australia 27%), but also among non-OECD countries (Singapore: 23%, Estonia: 22%, Belize: 21%, and Latvia: 21%).

Owing to the size of the phenomenon, immigration has been recently at the centre of the political and economic debate. Economists have studied extensively the potential impact of immigration on a variety of economic and social indicators of host countries, such as natives' wages (Borjas 2003; 2005, Ottaviano and Peri 2012) and employment opportunities (Pischke and Velling 1997, Card 2001; 2005), firm productivity (Peri 2012), trade creation (Gould 1994, Rauch and Trinidate 2002, Peri and Requena-Silvente 2010) and crime (Bell et al. 2010, Bianchi et al. 2012), just to take a few examples. Until very recently the effect of immigration on innovation and technical change was instead much less studied. Yet innovation is surely one of the key factors for a country's economic growth (Romer 1990, Aghion and Howitt 1992, Acemoglu 2002, Jones 2002).

Although new evidence is progressively accumulating, it remains nonetheless mostly limited to the impact of *skilled immigration* in the U.S. In recent work Hunt and Gauthier-Loiselle (2010) and Stuen et al. (2012), for instance, focus on skilled immigration —immigrant college population and doctoral students respectively— and find positive effects on U.S. innovation, measured by the count of patents or publications, and the citations they received.[1] Evidence that immigration may drive the direction of technological change is provided for the U.S. by Lewis (2011) who shows that plants in areas rich in immigrants adopted during the 80s and the 90s significantly less machinery, because of the relative abundance of less-skilled labour force. Consistent evidence is also reported for the same country by Peri (2012).

A related stream of literature expressely focuses on a specific aspect of immigration, the greater *cultural diversity* that it produces in the population. Ottaviano and Peri (2006) do not expressely focus on innovation, but on wages and rents; however, from the positive effect of immigrants' diversity on both variables they infer a positive effect on productivity of U.S. cities. A more direct focus on cultural diversity and innovation is provided by Niebuhr (2009) who analyzes German regions. She reports significant positive effects of cultural diversity in both total and high-skilled immigrants working in R&D — hence, the focus is again on skilled immigration — on patents percapita using instrumental variables (IVs, hereafter), but not when including region fixed effects. Except for the U.S. and Germany, published work for other countries is almost non-existent.

In this paper we make an attempt to contribute to this important stream of literature. In

[1] Other studies for the U.S. obtain similar findings. Chellaraj et al. (2008) find a positive effect of foreign students on patent applications using time-series data. Hunt (2011) finds that immigrants who entered the U.S. with certain types of visas —related to training, study, and temporary work— patent more innovation than natives. Kerr and Lincoln (2010) exploit the 1990 Immigration act and show that the increase in patenting from Chinese and Indian immigrants is positively correlated with H-1B type visas ('specialty occupations' requiring at least a bachelor's degree).

addition to providing evidence for a country which was exposed to a very fast and large wave of immigrations during the 2000s —Italy (see section 3)—, we also use a very small geographical scale of analysis —Italian provinces corresponding to NUTS-3 regions[2] — , which presumably enables us to better control for differences in institutional and socio-economic factors which are difficult to observe but which may simultaneously contribute to both attracting new immigrants and increase the innovation potential of a region. Moreover, unlike most papers in the literature which only considered the effect of skilled immigration, (i) we first focus on the general impact of immigration, and then (ii) separately look at the effects of low-educated and high-educated immigrants on innovation.

The structure of the paper is as follows. Section 2.1 sets the conceptual framework for our analysis. The existing work on the effect of immigration on innovation is surveyed in Section 2.2. Section 3 describes the Italian context and the main features of Italy's immigration, and Section 4 the data used in the empirical analysis. The main results on the effect of immigration on patents' applications are included in Sections 5.1 and 5.2, reporting OLS and IVs estimates, respectively. Section 5.3 extends the analysis by separately considering the differential effects of low-educated and high-educated immigrants. The last section summarizes our main findings, and concludes.

2 Immigration and innovation: Theory and empirics

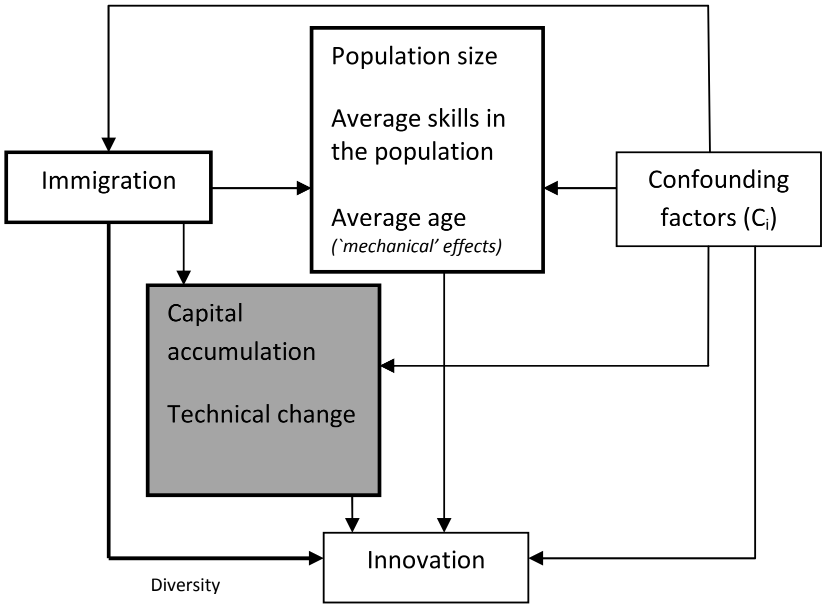
2.1 Theory and conceptual framework

There are several reasons why immigration may have an effect on innovation. Immigration entails an inflow of foreign population into a region, and produces changes (i) in the size of the population; (ii) in the average skill level of the population; (iii) in the age structure of the population, as immigrants tend to be of working age. The direction of the first two changes is unknown *apriori*, as new immigrants could increase the size of the population or decrease it in case natives abandon a region owing to the high concentration of immigrants, the so-called 'native flight' (on this specific point see Card and DiNardo 2000). The change in the average skill level in the population depends instead on the average levels of human capital of immigrants compared to that of natives. Both population and human capital are powerful predictors of innovation. Population is likely to spur innovation through the advantages produced by the agglomeration of economic activities (Becker et al. 1999, Glaeser 1999) and market size (Acemoglu and Linn 2004). Human capital is considered theoretically (Romer 1990) and found empirically (Faggian and McCann 2009, Andersson et al. 2009, Zinovyeva and Cowan 2012) an important input into the production of new ideas, and therefore innovation. Thus, population's size and average skill level are key *mediating factors* for the effect of immigration on innovation. The same can be said for the age structure of the population, from which we expect younger individuals to be more creative and innovative.[3] Since changes in these mediating variables due to immigrants' inflow are almost 'mechanical', i.e. they do not require economic agents (individuals, firms) to change their behavior, we expect their effect to be relevant also in the short run.

[2] NUTS stands for Eurostat Nomenclature of territorial units for statistics

[3] In fact, studies on the effect of population ageing on innovation are almost non-existent, while there is some evidence that older populations are less productive (Lindh and Malmberg 1999, Feyrer 2008).

Figure 1: Conceptual framework: Effect of immigrants on innovation



One aspect of immigration on which most of previous articles have focused is the fact that it produces a more culturally diverse population. Individuals coming from different countries usually have different, complementary skills with respect to natives, and the production of new ideas may be positively influenced by contacts and interchanges between culturally diverse individuals (Jacobs 1969). Moreover, a more 'diverse' cultural environment may attract more creative individuals (Florida 2002). Diversity is not necessarily an advantage though. Cultural diversity could also entail difficulties in communication, especially when immigrants and natives do not share the same language (as it is likely to be the case for low skill immigrants in Italy), reduce social capital, and act as an obstacle to innovation and growth (see, for istance, Alesina and La Ferrara 2005). Positive effects on innovation are expected mainly by diversity in the skilled population, and many studies have focused accordingly on skilled immigration only (see section 2.2).

However, there are other mechanisms through which one may expect negative effects of immigration on innovation. A large inflow of low-skilled immigration within a region may affect firms' choices concerning technology adoption and investments in physical capital. Lewis (2011) focus on U.S. metro areas, and finds 'that plants added technology more slowly between 1988 and 1993 where immigration induced the ratio of high school dropouts to graduates to grown more quickly' (p. 1031). Lewis also finds that the increases in the relative supply of low-skill workers are associated with slower growth in capital-labor and capital-output ratios. This work is likely to operate especially in the medium and long run, as it is related to technological change and physical capital accumulation. On the grounds of this recent evidence, we will not focus on skilled immigration only, but we will consider in our study both the effect of overall immigration and the separate effects of skilled and unskilled immigrants.

Hence, when considering the causal effect of immigration on innovation there are many potential pathways to be considered, some of which have opposite effects. The conceptual framework which will represent the starting point for our analysis is depicted in Figure 1. As we already pointed out, immigrants have an indirect effect on innovation through various mediating factors. These factors have been distinguished in two groups. 'Mechanical' factors are collected in the white box, while factors which requires economic agents to change their behavior in the grey box. Immigration also has a direct effect on innovation through cultural diversity. A first complication with this framework is that the variables in the two boxes of Figure 1 may also be affected by *confounding factors*. This happens if they depend on a 'third variable' which is also a determinant of immigration. An immediate consequence for the analysis is that although a common modelling approach to assessing the causal effect of immigration on innovation would be to omit *mediating factors* (i.e. post-treatment variables), this may generate an omitted variables bias in case they also are confounding factors. Just to take an example, immigrants may settle in large cities as they offer better employment opportunities, but these cities also benefit from agglomeration economies (the 'third variable'), which have in turn a positive impact on innovation. Omitting population from the analysis may then generate a spurious correlation between immigration and innovation, which is only driven by 'agglomeration economies'. Another example may be represented by positive shocks to the demand of low-skilled workers, which both change the product mix of a region, driving it towards more labour-intensive production processes, and the stock of low skilled workers in the region through immigrants' inflow (see Lewis 2011).

In what follows we write down the conceptual framework in a more formal way. Let us define the primary equation of interest, the determinants of innovation (y_{it}):

$$y_{it} = \beta_0 + \beta_1 imm_{it} + \beta_2 x_{it} + \beta_3 pop_{it} + u^y_{it} \tag{1}$$

where i and t are region and time subscripts, imm_{it} the share of immigrants on the population, x_{it} a vector of exogenous variables, pop_{it} population and u^y_{it} an error term. The share of immigrants is modelled as

$$imm_{it} = \lambda_0 + \lambda_1 x_{it} + \lambda_2 z_{it} + \lambda_3 c_{it} + u^{imm}_{it} \tag{2}$$

where z_{it} is a variable which enters the immigrants' share equation only ('excluded instrument'), c_{it} is another determinant of immigration, and u^{imm}_{it} an error term. If u^y_{it} and u^{imm}_{it} are correlated, then the share of immigrants is endogenous with respect to innovation. Let us now model population as a linear function

$$pop_{it} = \alpha_0 + \alpha_1 imm_{it} + \alpha_2 x_{it} + \alpha_3 c_{it} + u^{pop}_{it} \tag{3}$$

where u^{pop}_{it} is an error term. Pop_{it} is defined a *mediating factor* for imm_{it} if $\alpha_1 \neq 0$ and $\beta_3 \neq 0$. Pop_{it} is defined a *confounding factor* for imm_{it} if $\lambda_3 \neq 0$, $\alpha_3 \neq 0$, $\beta_1 \neq 0$ and $\beta_3 \neq 0$. This means that if pop_{it} is omitted from equation (1), its effect will be captured by imm_{it}. What are the modelling alternatives for the researcher? First, if pop_{it} is a mediating factor for imm_{it}, it is as endogenous as the latter variable is. Thus, in case mediating variables are included in the regression, they must be treated as endogenous variables, e.g., instrumented if the researcher uses an IVs strategy. Moreover, if all mediating factors are included, the researcher will estimate only the *direct effects* (e.g., 'diversity' in our conceptual framework) and not the *gross effect* of the independent variable ('treatment') of interest. Since it is difficult to find suitable instruments for all the endogenous variables, the researcher may be tempted to omit the mediating factors and focus on the gross effect ('gross-effect' approach), which allows her to focus only on the endogeneity of imm_{it}. As in this case the 'third variable' c_{it}, which makes pop_{it} a confounding factor, enter the error term of equation (1), instrumental variables will produce consistent estimates only if the excluded instrument z_{it} and the confounding factor

c_{it} are not correlated. In any case, also in this best case scenario, using the 'gross-effect' approach, the effects of imm_{it} and pop_{it} cannot be separately identified.

As we do not have instruments for all potential mediating factors (e.g., population, average skill level in the population, working age population) we focus on a slight modification of the 'gross-effect approach'. Although we do not include in the primary equation contemporaneous or one-period lagged potential mediating factors, we do include the value of these factors in a pre-estimation period (2001). The rationale for doing this is to try to control for time-invariant or very time-persistent confouding factors, avoiding at the same time to include variables which are likely to be affected by immigration during the estimation period. This also has the advantage of making the excluded instruments we use for immigration more credible. Indeed, we will use to build instruments for our main independent variables of interest (immigrants' share and diversity) a shift and share approach which is based on the distribution of immigrants by nationality across Italian provinces in 1995 and the idea of immigrant *enclaves* (see section 5.2). The main concern with this instrument is that also in 1995 immigrants (of all nationalities) may have located in more populated provinces, and since population is quite persistent overtime the instrument may be correlated with the error term in the innovation equation —if population is an important determinant of innovation— violating the instrument's exogeneity assumption. As we will see in the following section, in which we report a brief summary of the past literature, our approach partly differs from the one adopted by most researchers who have included potential mediating factors (e.g., population, human capital levels) in the estimation equation but treating them as exogenous variables.[4]

2.2 Past empirical evidence

The link between immigration, cultural diversity and economic performance has attracted considerable attention over the past decade. Most of the works in this field of research focused on the role of high skilled immigrants, defined in many ways. The impact of immigrants as a whole on host country's economic activity has been investigated only in Ottaviano and Peri (2006) and Prarolo et al. (2009). However, these works are not focused on innovation but, more generally, on the potential beneficial effects of a culturally diverse population on productivity. The analysis of Ottaviano and Peri (2006) aims to assess how diversity of American cities affects productivity, through its effect on natives wages and rental prices. Diversity is proxied by the 'fractionalization index'[5], initially computed for the whole population and then splitted in its two components: the share of immigrants and the index computed only for immigrants. The authors use a panel of U.S. metropolitan areas (MSA) for the years 1970 and 1990 and handle potential endogeneity of the share of immigrants with the 'shift and share' methodology: they construct their main instrument building on the fact that foreigners tend to settle in 'enclaves' where other individuals from their country already live. They use the share of residents in

[4] In the estimated innovation equation, Hunt and Gauthier-Loiselle (2010) consider for the population variable only its value at the beginning of the time period spanned by the analysis, but insert a contemporaneous variable for the average age of working age population. Measures of population size, composition of the working age population and human capital are included in the regression as contemporaneous variables in Ozgen et al. (2012) and Niebuhr (2009). However, none of these works took into account the possible endogeneity of these mediating factors.

[5] The 'fractionalization index' is also called 'diversity index' and is computed as the complement to one of a HerfindahlHirschman concentration index calculated on the shares of immigrants from different countries of birth. In the paper, we use indifferently one of the two terms to indicate the same index.

a MSA in 1970 for each country of birth and attribute to each group the growth rate of that group within the whole U.S. population in 1970-1990 time period. They compute the predicted composition of the city based on its 1970 composition attributing to each group the average growth rate of its share in the U.S. population. The predicted number of immigrants is then used to construct the instrument, that is the predicted diversity index. An additional instrument used in the IVs regression is the distance from the main gateways into U.S. The results show a positive effect of diversity on wages and rents, though the effect is mainly driven by the share of immigrants as a whole rather than diversity; the IVs estimates allows the authors to establish a causal relation between the presence of immigrants and productivity. Prarolo et al. (2009) find similar results for European regions (NUTS-3) from 12 countries of the EU15. Using a similar empirical framework, Suedekum et al. (2009) estimate the effect of diversity on natives' wages and employment in a panel of German regions (NUTS-3) during the period 1995-2006, but, differently from the above works, they try also to separate the effect of low skilled immigrants from that of high skilled immigrants (defined as those who have completed tertiary education). They use region and year fixed effects and address the endogeneity problem using second order time lags in addition to other instruments (fertility of regional foreign population, regional vote share of Green party and historical regional employment shares of classic guest workers industries, included in separate regressions). Their results highlight a negative effect of the share of immigrants and a positive effect of diversity on wages and employment, when all foreigners from a given country are considered as an homogeneous group. The analysis by skill level shows the two groups of immigrants affect productivity in an opposite way: the authors observe significant positive effects only when migrants are high skilled, while the effect of the share of low skilled immigrants is negative and drives the effect of total immigration.

When object of interest are the consequences of the changes in the 'ethnic' composition of population or labor force on innovation, mainly proxied by the number of patents applications, most of the existing studies focus only on high skill immigration, and basically refer to the U.S. context. In particular, U.S. based analyses do not take into account diversity as a potential driver of innovation (with the exception of Stuen et al. (2012)); they are more interested in the 'skill content' of immigrants. Chellaraj et al. (2008), using U.S. annual data for the period 1965-2001 (with regressors lagged 5-7 years), find a positive effect of skilled immigration and foreign graduate students on patents applications and grants. The share of skilled immigrants results to be beneficial for U.S. invention also in the work of Hunt and Gauthier-Loiselle (2010); they use U.S. state panel data for the period 1940-2000 (Census decennial data) and consider 10 to 50 years differences to account for short-run and long-run effects. They apply the same methodology as Ottaviano and Peri (2006) (shift and share) to create an instrument for the share of immigrants; the IVs estimate of the effect of the share of high skilled immigrants turns out to be larger than the OLS coefficient. Kerr and Lincoln (2010) analyze how the change in H-1B worker population influences ethnic patenting in U.S. cities during the period 1995-2008. They divide inventors in four groups according to their names and run separate regressions; according to their estimates, total invention increases with higher admissions of high skilled immigrants primarily through the direct contribution of Chinese and Indian inventors. The effect on native patenting is limited, but there is no evidence of displacement effects. Moser et al. (2011) finds a positive effect of German jewish *émigrés* on U.S. patenting during the period 1920-1970; changes in patenting are examined at the level of research fields, rather than locations. Pre-1933 research fields of dismissed scientists are used as instruments for the fields of U.S. émigrés; as in Hunt and Gauthier-Loiselle (2010) IVs estimates are larger than OLS estimates.

Stuen et al. (2012), analyzing American Science&Engineering departments from 1973 to 1998, try to identify the contribution of natives and foreign doctoral students to academic innovation, measured by publications and citations. The effect of foreign students on innovation turns out to be positive and significant, though not significantly different from that of natives. Using economic and policy shocks in the students' origin countries to instrument foreign enrollments the authors find that OLS underestimate the impact of foreign doctoral students, but again this effect is not statistically different with respect to natives. Also, they incorporate in the regression the 'fractionalization index' computed on regional shares to capture the degree of diversity in international doctoral students enrollments. OLS estimates shows that diversity has a positive and significant effect on both publications and citations, but the index becomes no longer significant with IVs. Overall, it seems that the beneficial effect of foreigners on innovation comes from their provision of a highly skilled workforce, not from cultural diversity *per se*.

Recently, similar studies have been developed also in the EU context.[6]. Bosetti et al. (2012) estimate a positive effect of the share of immigrants employed in top skilled occupations on patenting and scientific publications[7]. The shift-share procedure is exploited to create the predicted share of immigrants, which is the instrument for the main regressor in IVs estimation. An index measuring the tightness of national policy towards immigrations is used as additional instrument. Units of observations are 19 EU countries and the time period spans from 1997 to 2007. Other studies put particular interest on diversity as a potential determinant of innovation. Ozgen et al. (2012) does not focus only on high skilled immigration and considers, in separate regressions, the effect of the whole share of migrants and of population diversity (proxied by the fractionalization index) on innovativeness of EU regions, measured by patents applications. Further, he tries to separate the effect of low skilled migrants from that of high skilled migrants. Due to the lack of information about immigrants' skill levels, they group migrants on the basis of the average skill level of the 'global region' from which the are from (Africa, Asia, America, Europe and Oceania). The panel is composed of EU NUTS-2 regions; the variables are average values over two five-year periods (1991-95 and 2001-2005). The number of McDonald's per million of inhabitants, a dummy for presence of capital cities and the total area represent the instruments to handle the endogeneity of the share of immigrants (the diversity index is not treated as an endogenous regressor). Pooled OLS and IVs estimates show that the share of total immigrant is not significant, while the effect of population diversity turns out to be positive but non-linear. As for analysis by skill level, a higher share of skilled immigrants seems to be beneficial for innovation. The work of Niebuhr (2009) considers only German regions, but uses smaller units of observation (NUTS-3), and aims to establish a causal relationship between the diversity of the labor force and patents applications for the years 1997 and 1999. Again, the focus is on high skilled foreign workers; only R&D employees and high skilled R&D employees are included in the computation of the diversity index. Three different indexes are (separately) used to take into account diversity: the standard 'fractionalization index', the Theil index and the Krugman index. Lagged cultural diversity of low skilled workers in neighbouring regions and, as alternative, the lagged shares of foreigners in low skilled employment constitute the in-

[6] As for the European context, most of the studies in this field are conducted at firm level and are based on surveys data, basically CIS data (Ozgen 2011, Parrotta et al. 2011, Brunow and Blien 2011, Simonen and McCann 2008, Lee Neil 2010). Nathan (2011) analyzes the effect of diversity of inventor communities on individual patenting (panel of UK-resident inventor's patenting activities between 1993 and 2004).

[7] The number of citations is used in some specifications to account for patents' 'quality'.

struments for the diversity indexe in IVs estimations. Both OLS and IVs show a positive effect of diversity on patenting though this effect loses statistical significance once fixed effects are included in the regression.

From the review of the literature on the relation between migration and innovation, it does emerge that not only our work is the first one analysing the Italian case, but also that none of the previous papers involves at the same time very small geographical units of analysis (NUTS-3), the use of patents' data to proxy innovation, the analysis of the separate effects of low skilled and high skilled immigrants, and an attempt to address the endogeneity of immigration using a shift and share methodology to build instruments for both the share of migrants and the diversity index.

3 The country context[8]

Italy has been exposed to a very fast and large wave of immigration during the 2000s, as many other European countries. The share of foreigners on the Italian population grew from 2.7% in 2003 to 5% in 2007, though significant growth rates have been registered in North and Central Italy, while in the South the share of immigrants did not show relevant changes (Figure 5). At the beginning of 2007, foreigners accounted for 6.8% of population in Northern-Central regions, while they represented 1.6% of residents in Southern Italy. In fact, immigrant population results to be unevenly distributed across Italian territory; not surprisingly, foreign people moving to Italy tend to settle in the richer regions and in big cities, which offer better opportunity of employment; 86.9% of immigrants are concentrated in Northern and Central Italy, 23.2% live in Lombardy, 11.8% in Lazio, 19.2% just in the provinces of Milan and Rome. Nowadays foreigners are roughly 7% of total Italian population; in some areas in the Center and the North of the country they exceed the level of 10% [9].

Figure 3 shows a map of Italy where provinces are colored according to the share of foreign-born population in the total population, with 'darker' provinces hosting a higher share of immigrants. The map of Italy also reveals some spatial clustering of immigrants: provinces richer in immigrants are more likely to be close to each other.

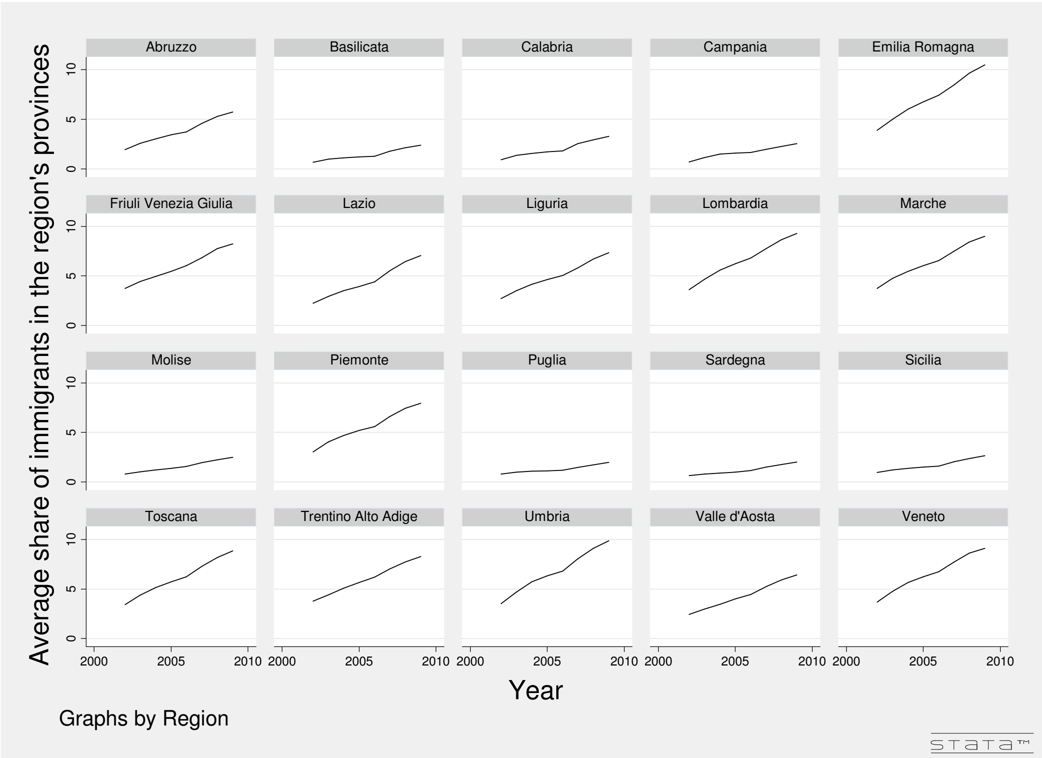
Foreigners turn out to be an important resource for the Italian economic system. In 2008 immigrants accounted for 12.1% of GDP formation; also, they are relatively young (32.6% of foreign employees is aged between 25 and 34, whereas for Italian employees the percentage is 20.9%) and represent 6.5% of entrepreneurs. However, the big majority of them tend to take manual-intensive and routine-type occupations (e.g. in construction, agriculture and personal-services sectors). One third of low skilled labor force is composed by immigrants (the share in high skilled workforce is 1.9%); 37.7% of foreign workers are employed in low skilled jobs (this percentage is 7.1% for Italian workers), 89.9% are blue collars. This is mainly due to low schooling levels that characterize most of foreign population in Italy, which fails to attract high skilled workers and students[10]. Apart from the fact that immigrants in Italy are prevalently low

[8]The main source of the information provided in this section is 'Rapporto annuale sull'economia dell'immigrazione - Edizione 2011', il Mulino.

[9]The percentage of foreigners on resident population is 12.9% in Brescia, 12.7% in Prato, 12.5% in Piacenza.

[10]Consider that the top five countries by the number of immigrants in 2009 were Romania, Albania, Morocco, China and Ukraine, accounting for about 50 percent of the total foreign-born population. According to Docquier-Markouf database (http://perso.uclouvain.be/frederic.docquier/oxlight.htm), the shares of high skilled emigrants (those with completed tertiary education) on total emigrants to Italy in 1991 and 2001 (basically constant across

Figure 2: Italy: Percentage of foreigners on total residents by region



Source: our data.

skilled, the Italian context is peculiar also in another respect: high educated immigrants often take low skilled job. It has been shown that, given similar characteristics (in terms of sex, age, education and experience), foreigners are three times more likely to fill low skilled positions. For low skilled jobs, firms seem to prefer immigrants: even if foreigners are 9% of the total workforce, they are more than 80% of agricultural workers, and represent 40% of workers in low skilled personal services and 18% of workers in the construction sector. This phenomenon has been called 'Job Ethnicization'.

The described situation is reflected on wages: immigrants' wages are 23% lower than Italians' and, differently from Italian employees, there seems to be no correlation between wage and the education level of foreign employees. To put it in other words immigrants are affected by substantial over-education.

So, it emerges that the characteristics of immigration in Italy are such that immigrants mainly appear as a source of low-skilled or cheap labour force, which is employed in traditional (i.e. low value added) economic sectors. As we will see later, this fact is very likely to be reflected on the role that immigration plays for Italy's innovation.

4 Data

Our dataset contains information on demographic and economic indicators for 103 Italian provinces (NUTS-3 level) and covers the time period 2002-2008. The main sources of data used in this study are ISTAT (Italian National Statistical Institute) and EUROSTAT. All data (except those regarding R&D intensity) are available at NUTS-3 level of aggregation. During the period covered by our dataset the number of Italian provinces has changed: the data are recorded according to 103 provinces before 2006 and to 107 provinces thereafter in the source databases[11]. So, data from 2006 onward have been reclassified in order to have 103 units of observation for the whole time period considered in our analysis. More precisely, the values referring to the four new provinces have been imputed to the provinces from which they 'exited' (so, for example, data post-2006 of Carbonia and Medio Campidano in Sardinia have been assigned to Cagliari).

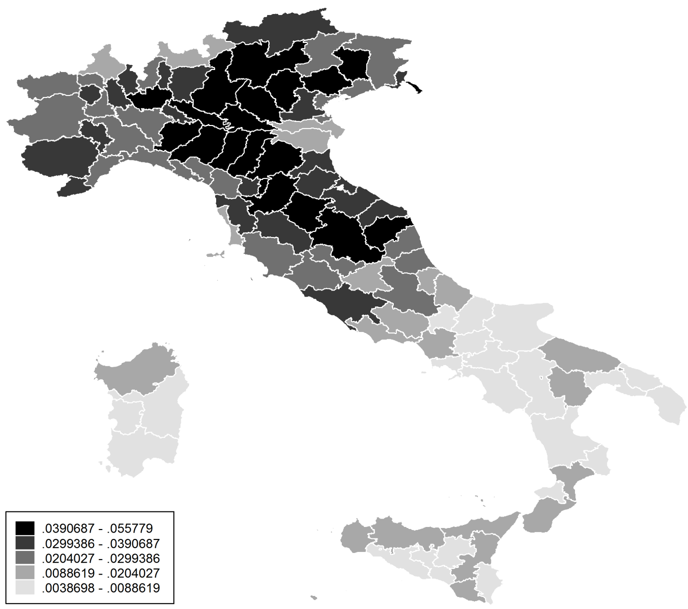
As a proxy for innovative performance of Italian provinces we use the number of patents applications to the European Patents Office (EPO)[12]. These data are available in the EUROSTAT database-Regional Science&Technology Statistics for the time period 2002-2009 at the NUTS-3 level of aggregation. However, available data for the year 2009 display a sharp decline with respect to the previous year, suggesting that these data are likely to be still incomplete. This potential problem, given the short time period covered by our dataset, may affect the results in a significant way; for this reason, in our regressions, the observations referring to this year are not included in the estimation. The EPO data used in this paper refer to all patents applications by priority year. Priority year refers to the first date the patent application was

the two periods) were 10% for Romania and Albania, 6% for Morocco and China, and 35% for Ukraine.

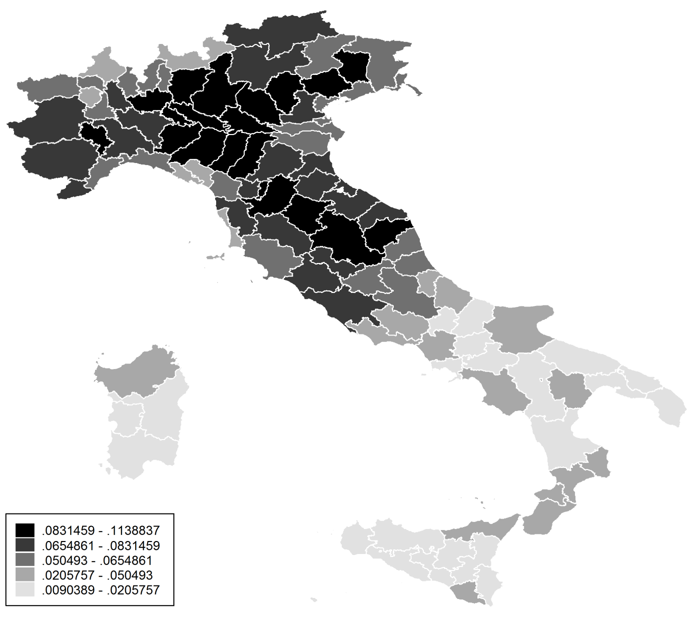
[11]The number of Italian provinces changed in recent times. In the mid 1990s the number of Italian provinces was 103. In 2001 the autonomous region of Sardinia established 4 new provinces, that became operative in 2005. In 2004 the Italian Parliament established 3 new provinces that became operative in 2009. The total actual number of provinces is 110. Since our dataset does not include observations for the years after 2009, the latter change does not affect our dataset.

[12]We use this information to build our dependent variable, that is the logarithm of patents' application per 1000 inhabitants.

Figure 3: Shares of immigrants in italian provinces, 2003 (Top), and 2008 (Bottom)



(a)



(b)

Note: Provinces with dark colors correspond to those in higher quintiles of the distribution. From the figure it can be noted that provinces with high (low) shares of immigrants tend to be clustered.

filed anywhere in the world. The OECD recommends using priority year as the closest to the actual timing of innovation. The distribution of patents applications is assigned according to the inventor's province of residence. If one application has more than one inventor, the application is divided equally among all of them and subsequently among their provinces of residence (fractional count), thus avoiding multiple counting. Using the residence of inventors rather than that of proponents (usually the headquarter) allows not to under-estimate peripherical regions innovation activity (Moreno et al. 2005) and makes more likely that innovations, related to the characteristics of the sorrounding territory, are imputed to the regions where they actually have been produced. Although they represent up to now the single best available measure of innovative output, commonly used in empirical research, patent numbers are an imperfect indicator of overall innovative activity. Griliches (1990) highlights the limitations of using patents as a proxy of innovation: (i) not all innovations are patented[13], thus patent data is only a partial indicator of innovative activity, (ii) not all patented innovations have the same level of quality[14], and (iii) propensity to patent changes across areas, sectors and time. As an extreme case, patents may even be an obstacle to innovation if they slow down the diffusion of knowledge or pose prohibitive barriers to market entry. International comparisons are also affected by differences in procedures and standards across patenting offices. Despite all the above mentioned limitations, patents continue to be considered the most reliable measure of innovation output. Moreno et al. (2005) argue that applications to EPO account for patents of homogeneously high quality, because applying is difficult, time consuming and expensive, so the related innovations are likely to be potentially highly remunerative. The problem arising from the fact that different sectors have intrinsecally different propensities to patent can be handled by controlling for the industrial structure in regression analysis, as we do. Moreover, there seems to exist a positive relationship between patent counts and other indicators related to innovative performance (OECD Patent Statistics Manual).

Figure 4 gives an idea of the distribution of patents applications across Italian provinces. It is evident that patents applications are not evenly distributed and a clustered pattern emerges: provinces with higher patents applications per 1000 inhabitants are located close to each other. A similar pattern could be found in the distribution of immigrants across provinces (see section 3)[15].

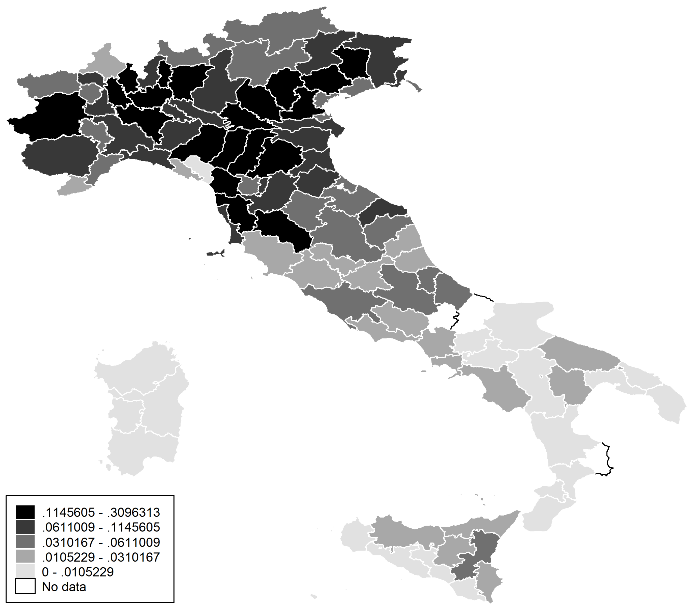
The two variables used in our analysis to assess the impact of immigration on innovation are the share of immigrants on resident population and the 'diversity index', an indicator that accounts for the 'variety' of a province's population (the construction of the index is described in subsection 5.1). Immigrants are defined as residents born abroad with a foreign nationality. Data on foreign born residents by province (NUTS-3) are taken from the demographic portal of ISTAT, that contains information on the stock of legal immigrants from 195 country of origin (home-country) resident in each province at 31 of December. Although in this paper like in all the related literature we only consider immigrants with legal status, Bianchi et al. (2012) considering the demands for regularization presented in 1995, 1998 and 2002 show that the

[13] For example firms often choose to keep secret innovations that are strategic or commercially sensitive, or some innovations are simply non-patentable.

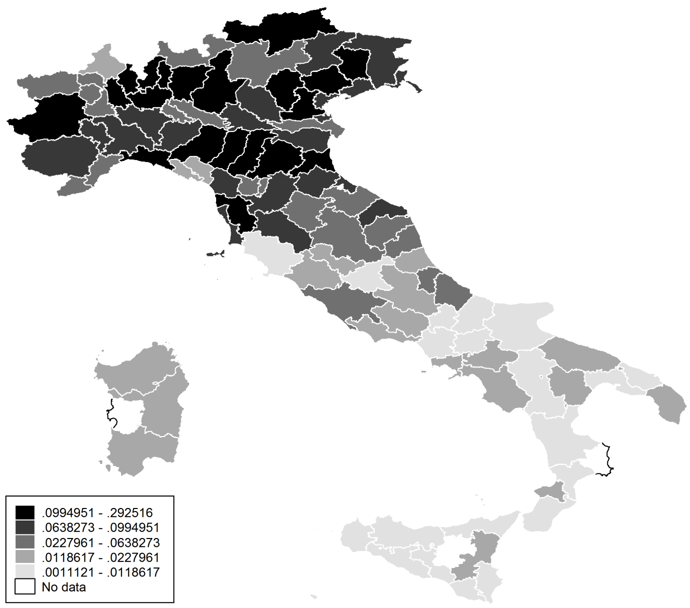
[14] However there are no generally recognised, easily applicable methods for measuring the value of patents. Some authors (Bosetti et al. 2012, Stuen et al. 2012) used the number of citations to account for patents' 'quality'; in our case, given the short time period covered by our dataset — 6 years — and the (not negligible) time lag between applications and grants, it would not be clear how to use this kind of information.

[15] We will take into account this fact in our analysis by correcting the standard errors through the cluster option.

Figure 4: Logarithm of patents per capita in Italian provinces, 2003 (Top) and 2008 (Bottom)



(a)



(b)

Note: Different colors account for the quintile to which each province belongs; darker colors represent higher quintiles.

distribution of regular and irregular immigrants are tightly related, and that the ratio of the two is very stable within provinces and (regularization) years. Here a clarification is worth to be done. As mentioned before, in analyzing the effects of immigration on innovation, an important aspect is the degree of diversity immigrants bring to the community in which they decide to settle. 'Cultural diversity' is what could affect positively (complementarities) or negatively (increased transaction costs) the efficiency of an economic system. Unfortunately, there is no general agreement on the criteria to distinguish 'cultural groups' within the population; language, race, natural origin or other characteristics are alternatively taken into account in related studies[16]. However, Ottaviano and Peri (2006) show that, for the U.S., measures of urban diversity based on country-of-birth, language-spoken-at-home, citizenship and race are highly correlated across cities. Given the information in our dataset, we use the country of origin as the indicator of cultural identity used to compute the 'diversity index'. Information on immigrants disaggregated at level of country of birth is also the reference point to construct the instruments for IVs estimation, based on the shares of immigrants from 195 countries in each province in 1995; data regarding the distribution of immigrants by country of origin across provinces in 1995 are provided by the Italian Ministry of Interior (foreign residence permits).

To build the time-varying control variables used in the regressions, we relied upon the dataset 'ISTAT-*Sistemi Indicatori Territoriali*' (Systems of Territorial Indicators). We took data on the value added generated by each province divided by sector (agriculture, services, manufacturing and construction) to construct the shares of valued added accounted by each sector; this should allow us to control for the provinces' industrial structure and so for different propensities to patent across sectors. These variables are included in the regression as contemporaneous variables since the industrial structure might be affected by immigration, but this is likely to happen only in the long run (industry structure is very persistent overtime); so endogeneity issues are less likely to arise for this variable. Data on value added are available only until 2007; however, since we lagged by one year all the time-varying covariates, this does not represent a problem for our estimates. From ISTAT databases are also the data we used to build the time-invariant (2001 values) control variables (resident population, working-age population and number of graduates[17].).

Finally, data on R&D expenditure as percentage of GDP are not available at NUTS-3 level of aggregation; we took the data at the NUTS-2 level (corresponding to Italian regions) and assigned to each province the R&D expenditure of the region to which it belongs.

5 Empirical strategy and main results

5.1 Ordinary least squares

Following the discussion in section 2.1, we propose the following linear specification of the data generating process of patents' applications,

$$\ln PATN_{ijt} = \alpha_0 + \delta_t + \delta_j + \alpha_1 MIGsh_{it-1} + \alpha_2 \mathbf{X}_{it-1} + \alpha_3 \mathbf{X}_{jt-1} + \alpha_4 \mathbf{D}_{i2001} + \varepsilon_{ijt} \quad (4)$$

[16]Also the level of aggregation is often different. For example Prarolo et al. (2009) use information about country of birth to aggregate the immigrants in larger groups: EU countries, Africa, America, Asia, Oceania (and a residual 'unknown' group). Ozgen et al. (2012) operate a similar aggregation.

[17]The number of graduates is from the 2001 Population Census

where i, j and t are province (NUTS-3), region (NUTS-2) and time subscripts, respectively. $\ln PATN_{it}$ are patents' applications per 1000 inhabitants in logarithms; δ_t and δ_j are year and region (NUTS-2) fixed effects; $MIGsh_{it-1}$ is the share of immigrants on the population; $\mathbf{X}_{it-1}$ is a vector of time-varying province characteristics, including the provinces' industrial structure (the shares of valued added accounted for by agriculture, construction and services)[18]; $\mathbf{X}_{jt-1}$ includes the R&D intensity on regional GDP (the same variable is not available at the NUTS-3 level). $\mathbf{D}_{i2001}$ is a vector of covariates which may represent both mediating and confouding factors, and whose values have been included at a year pre-dating the estimation period (2001): population size, the share of active age population and the college share in the population, as a proxy of human capital. All these latter variables are expected to have a positive effect on innovation. Our patents' data spans the years 2003-2008 (6 years), and has a panel structure. Since for some years information on patents' applications is not available for all provinces, we have a unbalanced panel of 607 observations.[19] All time-variant regressors have been lagged one period to make them predetermined with respect to the dependent variable. ε_{it} is an error term. As in the regression we are including some covariates which are more aggregated with respect to the panel unit of analysis (i.e., $\mathbf{X}_{jt-1}$), the standard errors are clustered at the region by time level (Moulton 1990). Clustering observations by region allows for both spatial correlation of regressors between provinces within the same region, and partly accounts for the clustering of parents and immigration observed in figures 4 and 3.

In analogy with the study of Ottaviano and Peri (2006) on the effect of immigrants' diversity on wages and rents, we do not limit our analysis to skilled immigrants only, like most previous literature did, but consider all immigrants irrespective of their educational level. Indeed, although skilled immigration is expected to have a positive impact on innovation (see section 2.1), this does no exclude that unskilled immigration can have a negative effect by reducing social capital, creating communication problems among workers or pushing firms to lower their efforts to introduce product and process innovations. Firms located in provinces rich in low skilled immigrants might indeed concentrate on the production of traditional (low-value added) goods, using production processes which make a more intense use of unskilled labour. Including all the immigrants, irrespective of their skill level, allows us to assess their overall impact on provinces innovativeness.

One thing is worth noting. Because of the short time interval spanned by our data, we preferred not to include in the *benchmark* specification (4) province fixed effects. $MIGsh_{it}$ is quite persistent overtime, and the within estimator would use only very limited time variation in this variable.[20] We use a mid-way approach. Indeed, we do not include NUTS-3 fixed effects but we do include NUTS-2 fixed effects. This enables us not only to use time variation but also *cross-sectional variation between provinces within the same region*. Region fixed effects, in turn, enable to catch all potential unobserved differences existing across Italian regions, which are likely to be important especially because of the strong North-South geographical divide. [21]

[18]The main rationale for including this variable is that a province's patenting capacity is likely to be highly correlated with its industrial structure — as the degree of innovation strongly differs across industries (Klevorick et al. 1995) — which is in turn correlated with immigrants' employment opportunities and geographical location.

[19]Out of a 618 (103 provinces multiplied by 6 years) theoretical number of observations.

[20]This problem is stressed, for instance, in Niebuhr (2009), who dismisses the results of the fixed effects model because of the very low time variation in her data, and the potential large attenuation bias caused by measurement error.

[21]A similar approach is used, for instance, by Wagner et al. (2002) and Bratti et al. (2012), in their analyses of the effect of immigration on trade. Small-level Fixed-effects specifications are instead used by the authors who

For the same reason, owing to the short time span considered, our estimates only refer to the *short- and medium-run effects of immigrants on innovation*.

As a proxy of the diversity of a province's population we do not only use the immigrants' share, but also the so-called Ethnolinguistic Fractionalization (ELF) index (Mauro 1995), specifically:

$$POPdiv_{it} = 1 - \sum_{g=1}^{G_{it}} \left(\frac{P_{git}}{P_{it}} \right)^2 \tag{5}$$

where g is the subscript for country of origin, G_{it} the total number of countries (including Italy since also natives are considered as an ethnic group) present in province i in year t, P_{git} the population of ethnic group g residing in province i at time t and P_{it} the total population of province i at time t. The value of this index is determined both by the 'richness' (number of groups) of the local population and by its 'evenness' (similar distribution of individuals across groups), and can be interpreted as the probability that two randomly drawn individuals in the population will not belong to the same ethnic group. Higher values of the index means a more diverse population. As a matter of fact, most of the variation in $POPdiv_{it}$ is driven by the share of immigrants in a province, and a simple OLS regression of the former on the latter returns an R-squared of 0.99[22].

Table 1 reports the OLS estimates. Column (1) shows the specification without control variables. A very significant correlation between the share of immigrants and patents' applications emerges. Rising the share of immigrants by one percent point (p.p.) is associated with a 0.36 percent increase in patents' applications (per 1,000 inhabitants); however, provinces' unobserved factors could be responsible for this correlation. In column (2) we control for year and region fixed effects. The coefficient on the share of immigrants is one third the one in column (1) and the R-squared increases by 0.30, suggesting that a great deal of the variation in patents' applications is accounted for by regional differences and time trends. In column (3) we add two important potential determinants of innovation, R&D intensity on GDP and the province's industrial structure. Inclusion of these further controls has little effect of the coefficient of immigrant share, confirming that immigration flows have no relevant correlation with both the industrial structure and R&D at least in the short and medium term. Column (4) reports our *benchmark* specification, which includes variables which may act as both confounding and mediating factors for the effect of immigration: log population, the share of active age population and the college share in the province. We try to isolate their mediating role by including their values in 2001, i.e. before the estimation period, so as they are not affected by changes in immigrants' shares. All three variables turn out to be key determinants of patents' applications, and more importantly the coefficient on the share of immigrants is greatly reduced in magnitude, changes in sign, falling to -0.017, and becomes statistically insignificant. These results suggest that in the previous columns immigrants' share may be picking up the fact that immigrants tend to settle in highly populated provinces, in provinces with higher shares of active age population and college graduates, provinces which are *ex-ante* more innovative. In column (5) we use the population diversity index instead of the share of immigrants, and the results are very similar.

consider Census data and a long time span (see, for instance, Hunt and Gauthier-Loiselle 2010).

[22]The diversity index computed including natives can be considered as composed by two parts: the share of immigrants on the population and the diversity index computed only on foreigners. In the regressions for wages and rental prices, Ottaviano and Peri (2006) consider first the overall index and then separately its components, concluding that the positive effect found for the overall index is mainly driven by the share of immigrants.

5.2 Endogeneity and identification: Two-stage least squares estimation

OLS give consistent estimates only if, conditional on the observables included in the innovation equation, the error term is uncorrelated with the immigrant's share. There may be several reasons why this assumption fails. It may happen, for instance, that shocks to local demand, e.g. an increased foreign demand for a low-skilled good produced in the province, will attract more immigrants locally and also have negative consequences for innovation. Identification of the effect of immigrants requires therefore a presumably exogenous shock in the supply of immigrants at the province level. The shock does not necessarily need to be completely random, but uncorrelated with the innovation capacity of a province.

Here, to build an 'instrument' for the share of immigrants on the population we follow the procedure proposed in Altonji and Card (1991), which has been already intensively employed in the empirical literature on immigration (see, for some recent applications, Hunt and Gauthier-Loiselle 2010, Lewis 2011, Peri 2012), and is based on *immigrants' enclaves*. The idea is that immigrants tend to settle where individuals of the same nationality are already located. This may happen for a variety of reasons. For instance, immigrant networks may provide newly arrived individuals with important information on the local labour market and the availability of job vacancies, increasing the returns to migration, or providing hospitality thereby reducing the costs of migration[23]. Although $MIGsh_{it}$ relates to the total share of immigrants on the population, separate information by country of origin is provided by the Italian National Statistical Institute (ISTAT). Our instrument has been built as follows. We took the yearly stock of immigrants by nationality in Italy as a whole (M_{gt}) and imputed it to provinces (M_{git}) according to the distribution of nationalities across provinces in 1995 (θ_{i1995}), computed using foreign residence permits data provided by the Italian Ministry of Interior[24]:

$$\widehat{M}_{git} = \theta_{i1995} M_{gt}. \tag{6}$$

We then aggregated at the province level all immigrants' predicted stocks by nationality ($\widehat{M}_{git}$) across all nationalities present in each province in 1995 (G_{i1995}) to compute the total stock of immigrants of province i at time t, and divided the latter by the predicted total province's population obtaining the instrument, the predicted immigrants' share ($\widehat{MIGsh}_{it} = (\sum_{g=1}^{G_{i1995}} \widehat{M}_{git})/\widehat{POP}_{it}$). As we did for immigrants, also the predicted total population $\widehat{POP}_{it}$ was computed apportioning to provinces the population of each year according to the 1995 provincial distribution to account for its potential endogeneity.

The same procedure was followed to compute an instrument for population diversity. Indeed the predicted stocks of immigrants by nationality can be used to compute a 'predicted' ELF index[25] (see Ottaviano and Peri 2006):

[23]This holds in particular for low skilled migrants. Beine M. (2013) show that the elasticity of migration shares with respect to the diaspora is positive for unskilled migrants and negative for skilled migrants

[24]As disaggregated data on residents by foreign nationality is only available for Italian provinces since 2002 through the Italian National Statistical Institute (ISTAT). We focus on 1995's data as in that year there were 103 provinces, while the number of provinces was 95 before. The residence permit can be defined as the administrative act by which the alien lawfully entered the territory of the State is allowed to settle in Italy for a specified period. Foreigners who intend to stay in Italy for a period less than three months (ie short-term stays) and who enter the country with a visa for reasons of visit, business, tourism and study should not require the issuance of a permit of stay.

[25]Predicted natives are computed as the difference between predicted population and the predicted total number of immigrants.

$$\widehat{POPdiv}_{it} = 1 - \sum_{g=1}^{G_{i1995}} \left(\frac{\widehat{P}_{git}}{\widehat{P}_{it}} \right)^2 . \quad (7)$$

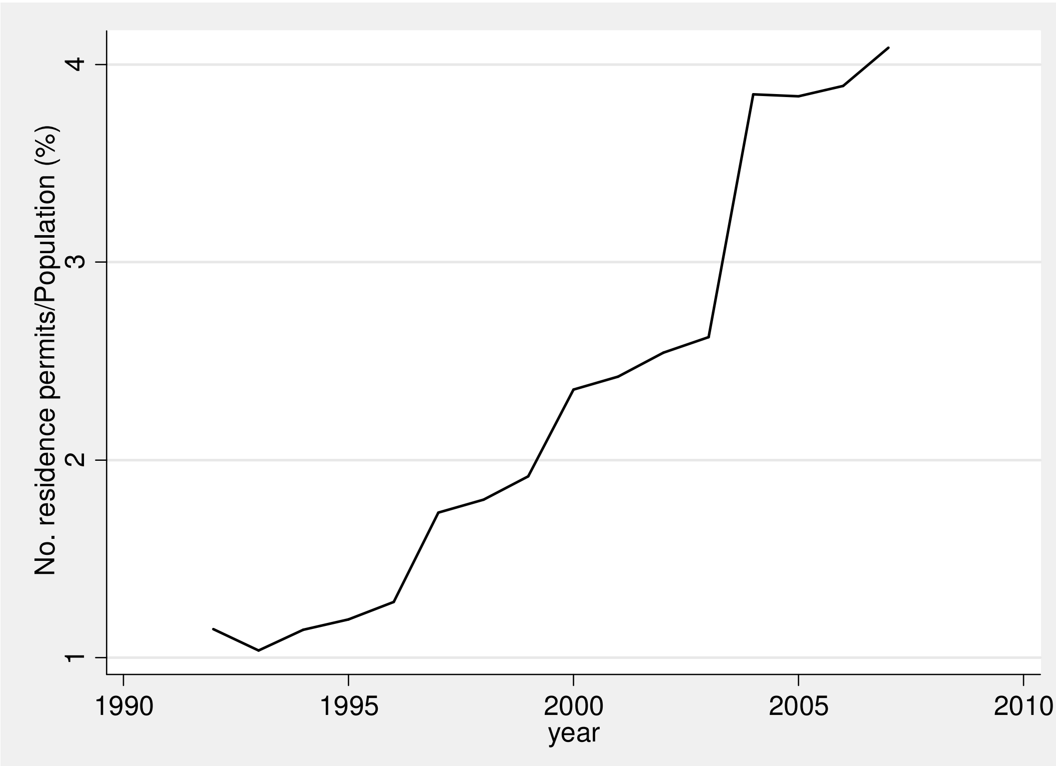
Both instruments are based on two components. The first is the total stock of individuals by nationality in Italy, which should be uncorrelated with single provinces' supply and demand shocks impacting on local innovation. The second component is the distribution of immigrants and of the total population in 1995. We claim that the distribution of immigrants (or the population) in 1995 should be uncorrelated with *unobserved factors* affecting patenting more than 7 years later, conditional on the observables we included in the regressions. The main identifying assumption is that, conditional on the observables, within-region differences[26] in the distribution of immigrants by different nationality in 1995 are approximately random with respect to provinces' future innovation prospects. We posit that the main factors which could be responsible for very persisting differences in innovativeness across provinces are their industrial structure, and the existence of agglomeration economies, both of which have been controlled for in our *benchamark* specification. Moreover, figure 5 shows that until 1995 the percentage of foreign residence permits in the population was quite constant overtime, and that 1995 pre-dates the period of rapid inflow of immigrants in Italy. This suggests that the instrument is likely to be orthogonal to potential demand shocks which might persist during our estimation period, since in that case we should have observed a much steeper increase in immigrants inflows around the base year.

Table 2 reports the 2SLS results. In all cases we adopted the *benchmark* specification and clustered the standard errors at the region by time level. In column (1) we use the predicted share of immigrants. The F-test in the first stage is quite high at 181.76, confirming the strength of the excluded instrument (the predicted share of immigrants). The instrument's t-value is 13.48, and the coefficient is 0.38 suggesting that although immigrant *enclaves* contributes to explaining immigrants' location, there are other factors which also affect immigrants' choices of residential location. From the second stage we estimate that a one p.p. increase in a province's immigrant share reduces patents' applications per 1,000 inhabitants by 0.06 percent. In column (2), we use the ELF index. The first stage is equally strong with an F-test of 170.56. From the second stage we estimate that a one-standard-deviation (0.047) increase in population diversity reduces patents' applications by 0.16 percent.

The results in this section suggests that, at least for Italy, immigration has overall a negative effect on innovation, proxied by patents' applications per 1,000 inhabitants. This finding is likely to be the result of the characteristics of Italian immigration which, as we outlined in section 3, is prevalently unskilled. As a matter of fact, almost all studies who have found a positive effect of immigration on innovation have focussed on skilled immigration, e.g., immigrants with a university education (Hunt and Gauthier-Loiselle 2010, Stuen et al. 2012) or working in skilled occupations (Kerr and Lincoln 2010, Niebuhr 2009, Bosetti et al. 2012). For this reason, in the following section we try to investigate the separate effects on innovation of high skilled and low skilled immigrants. Our prediction is that the overall negative effect is mostly driven by (i) a negative effect of low educated immigrants on innovation and (ii) the prevalence in Italy of unskilled immigration.

[26]Since we control for region fixed effects.

Figure 5: Italy: Foreign residence permits (% of population) 1992-2007



Source: ISTAT

5.3 Differences by immigrants' skill levels

The 2SLS results in the previous section suggests that the overall share of immigrants and the 'diversity' they create in the society have a negative impact on Italian provinces' innovativeness. This could seem to be at odds with the existing literature, but we have to keep in mind that we were considering immigrant as whole, while previous works, mostly concordant in finding a positive effect of immigrants on innovation, were restricting the analysis only to a subset of the immigrant population, namely its high skilled component. Actually, our estimate of an overall negative effect may hide more complex dynamics related to the large heterogeneity in immigrants' levels of skill, which can generate different effects working in opposite directions. For this reason, in the current section we try to disantangle the (possibly different) effects on innovation of low skilled and high skilled immigrants. To this aim, we need to split the population of immigrants resident in each province into its high skilled and low skilled component. Unfortunately, our dataset does not contain information that can be used to infer the skill level of immigrants (such as the level of education or occupation), so we had to rely on external data and some simplifying assumptions. We used the dataset provided by Docquier and Marfoukof[27], which contains detailed information on international migration by educational attainment. This dataset provides the number of emigrants to Italy in 1991 and 2001 from 195 countries, divided in low, medium and high skilled. The authors count as migrants all working-aged (25 and over) foreign-born individuals living in an OECD country; high skilled migrants are those with at least tertiary educational attainment wherever they completed their schooling[28]. We took the data regarding 2001, that have less missing values, to compute for each country of origin the share of medium-high skilled emigrants on total emigrants to Italy[29]. Then, we used two different procedures to assign the skill level to individual immigrants, in order to create the shares of low skilled and high skilled immigrants for each province[30]. The first procedure consists in dividing the immigrants between high skilled and low skilled according to their country of origin, that is, after having classified a given country as source of high or low skilled immigrant, we impute the same skill level to all the immigrants from that country[31]. We define a country as a source of high skilled individuals if its share of medium-high skilled emigrants to Italy is larger than the median value (0.56). With the second procedure, we tried to divide the immigrants by skill level in a more precise way. In this case, the total number of immigrants from a given country is splitted by skill level according to the shares of high-medium skilled and low skilled emigrants on total emigrants from that country to Italy. We run separate regressions to estimate the coefficients of the variables created according to the described procedures, obtaining similar

[27]http://perso.uclouvain.be/frederic.docquier/oxlight.htm

[28]Medium and low skilled migrants are those with secondary and primary education respectively. The source of these data can be different according to the country of origin of migrants. Detailed information can be found in the document 'International Migration by Educational Attainment (1990-2000) - Release 1.1' by Frédéric Docquier and Abdeslam Marfoukb, p.14. http://perso.uclouvain.be/frederic.docquier/oxlight.htm

[29]We refer to the share of medium and high skilled to obtain information about the immigrants that will be defined 'high skilled'; this is justified by the fact that natives' average level of education is the medium one, so, with respect to the Italian case, immigrants whose education level is not lower than medium can be classified among the high skilled workforce.

[30]In the regressions by skill level the diversity index is not taken into account as we have seen in the previous section that most variation in the diversity index is driven by the share of immigrants.

[31]A similar procedure is followed by Ozgen et al. (2012) wh0 group migrants on the basis of the average skill level of the 'global region' from which they are from (Africa, Asia, America, Europe and Oceania). We consider here a finer classification using individual countries of origin.

results, which will be discussed below[32]. To build the instrumental variables $\widehat{MIGsh}_{it}$ for the two groups, high skilled and low skilled, we started by the ‘predicted number of immigrants’ in a province from a given country, obtained using the ‘shift and share’ method described in section 5.2. We then applied to the ‘predicted number of immigrants’ the two procedures described above, in this case using data of 1991 in the Docquier-Marfoukof database, and get the ‘predicted high skilled immigrants’ by nationality. Summing up this latter for each province across nationalities and dividing by the province’s predicted population we obtained the instrument for the share of high skilled immigrants (‘predicted share of high skilled immigrants’). In the same way we computed the ‘predicted share of low skilled immigrants’.

We estimated the *benchmark* model using the lagged share of low skilled and the lagged share of high skilled immigrants instead of the lagged share of immigrants as a whole. For the sake of completeness we report the results of both OLS and 2SLS estimates; Table 3 displays the regression output for the case in which the variables related to immigrants are computed with the first procedure, while Table 4 refers to the second procedure. OLS estimates of the coefficients of the lagged share of high skilled and low skilled immigrants are not significant, whatever the skill level of immigrants and the procedure adopted to split them is. The sign of the coefficient of the share of low skilled immigrants is always negative, while the sign of the coefficient on the share of high skilled immigrants becomes non-negative (actually very close to zero) when they are computed according to the share of medium-high skilled emigrants from their country of origin to Italy. Given the endogeneity of the variables related to immigrants (see section 5.2), we also estimate an IVs regression. Results from the first stage confirm also in this case the strength of the instruments: the F-tests take value 57.78 for the share of high skilled immigrants and 176.88 for the share of low skilled immigrants, when the the first procedure to split the immigrants is used; as for the other procedure, the corresponding values of the F-tests are 70.63 and 165.81. The excluded instruments are highly significant, with the exception of the predicted share of low skilled immigrants in the first stage regression for the share of high skilled immigrants, when the first procedure is used to divide immigrants by skill level (Table 3)[33]. In the second stage, the coefficient of the share of low skilled immigrants is negative and significant. In the case in which we use the first criterion to define ‘high skilled countries of origin’ (Table 3) the stock of immigrants is significant at 1% and indicates that an increase of the share of low skilled immigrants of one percent point induces a decrease in patents’ applications per 1,000 inhabitants of 0.09 percent. In the case in which immigrants from the same country of origin are divided in high skilled and low skilled (Table 4) using

[32]We tried also a finer division of immigrants in three groups (low, medium and high skilled); results do not change significantly, confirming the negative and significant effect of low skilled immigrants on patents’ applications.

[33]The difference in magnitude of the values of the F-test for the first stage regression for low skilled and high skilled immigrants and the significant negative sign of the coefficient of the predicted shares of high skilled immigrants in the first stage regression for the share of low skilled immigrants can be explained in the light of the findings of Beine M. (2013). They show that networks favor the migration of less-skilled migrants rather than skilled migrants. Diasporas exert greater effects on the flows of unskilled workers for two reasons: (1) the decrease in migration costs is larger for unskilled workers; (2) diasporas favor family-reunification processes that are more important for unskilled workers. So, diasporas should increase the proportion of unskilled migrants at the destination. Accordingly, immigrants enclaves turn out to be a better predictor for the share of low skilled immigrants. They also find that the more educated the existing diaspora is, the lower the proportion of less-skilled migrants. From this result they infer that the network effect might be higher for migrants with the same level of education, since the informational value of the network depends on the degree of matching between new and old migrants.

the second criterion, the coefficient on the share of low skilled immigrants is significant at 5% and double in magnitude: a rise in the share of low skilled immigrants of one p.p. generates a reduction in patents' applications per 1,000 inhabitants of 0.19 percent. The coefficient of the share of high skilled immigrants is positive but not significant in both cases; it suggests an increase in patents' applications per 1,000 inhabitants in a range between 0.03 and 0.11 percent (according to the method used to divide immigrants between skill levels) following an increase of 1 p.p. in the share of high skilled immigrants, but this effect is not precisely estimated in our sample. These results are consistent with the analysis of Lewis (2011) and Peri (2012); they find evidence that a rise in the supply of low skilled workforce caused by large inflows of foreigners hampered investments in physical capital in the U.S. and favored the adoption of labor-intensive production technologies, thus reducing firms' incentives to innovate. The strongly significant negative effect of low skilled immigrants and the fact that the positive impact of high skilled immigrants turns out to be not significant in our regressions can be explained by the particular features of the immigration phenomenon in Italy, characterized by large prevalence of low educated immigrants and the under-utilization of immigrants' human capital. This point will be further discussed in the concluding section.

6 Concluding remarks

In this paper, we have investigated the effect of the share of immigrants in the population and of the population diversity (enhanced by immigration) on Italian provinces' patent applications, as a proxy for innovation performance. We aim to address the potential endogeneity of these variables by employing a well established procedure in the literature based on immigrants' enclaves, which uses a 'shift and share' approach. Differently from most work in this literature, we do not limit the analysis to the effects of skilled immigration, but we look at the general impact of immigration, and at the separate effects of low-educated and high-educated immigrants on innovation. This choice has been determined by the consideration that, in addition to possible positive effects on the production of new ideas arising from skills' complementarities, the most recent contributions have suggested that there may also be adverse effects on innovation generated by the inflow of foreign population (Lewis 2011). Increasing transaction and communication costs, reduction of social capital and the scarce incentive to the adoption of new capital-intensive technologies, owing to the abundance of cheap low-skilled labor force, may all act as obstacles to innovation and growth, in particular when immigrants are characterized by low levels of education and skills. We have shown that this is likely to be the case of Italy, which mostly attracts low-skilled immigrants who are employed in traditional sectors. So, excluding the low skilled component of immigration from the analysis would give a very misleading picture of the *overall* effect of immigration on innovation. Indeed, our analysis suggests that as far as total immigration is concerned, the positive association between the presence of immigrants and patenting, dominant in the past literature focused on skilled migration, does not emerge in Italian provinces. We find an overall negative effect of the share of immigrants and of population diversity: rising immigrants' share by 1 p.p. produces a 0.064 percent reduction in patents' applications per 1,000 inhabitants. Investigating the separate effects on innovation of high skilled and low skilled immigrants, our results support the hypothesis that the overall negative effect is mostly driven by a negative effect of low educated immigrants on innovation (consistent with the findings of Lewis (2011), Peri (2012) and Suedekum et al. (2009)), and the prevalence in Italy of unskilled immigration. Indeed, the impact of low skilled immigrants turns out to be negative and highly significant, while the effect of high skilled immigrants, though positive, cannot be precisely estimated. A one p.p. increase in the share of low-skilled immigrants is estimated to cause a reduction in patenting activity in the range between 0.094 and 0.186 percent, according to the procedure used to assign immigrants to skill groups. The fact that the positive impact of high skilled immigrants turns out to be positive but not significant can be explained by the particular features of immigration phenomenon in Italy. We have seen that not only Italy mainly attracts unskilled immigrants, but also high-skilled immigrants are often employed in traditional sectors and fill low-skilled jobs, suffering from substantial overeducation. So, due to the scarce presence of educated immigrants and the 'waste' of their human capital, the (potentially) positive effect of high skilled immigrants on innovation does not emerge in our country and results to be overshadowed by the negative effect of low skilled foreign population.

Our results point to the importance of immigration policies, given the assessed impact of foreign population on a main driver of economic performance, and the importance of a correct functioning of the labour market in order to grant a good match between immigrants workers' skill levels and the work positions they fill. This should allow Italy to exploit the innovative potential arising from the presence of skilled foreigners, as other countries seems to do. Also, given the short period spanned by our data, all the effects we estimated should be interpreted as medium-run/short-run effects and this does not exclude that, considering longer periods, additional effects on the economy may emerge, for instance mediated by physical capital accumulation and technological change (Lewis 2011). This is particularly important because the negative effect of low skilled immigrants on innovation can intensify in the long run, if the economic system adapts its technological choices to the availability of a large share of unskilled workforce. A greater exploitation of the competencies of skilled immigrants and the valorisation of their human capital could help to compensate the discussed short and long run negative effects, by attracting educated immigrants, giving complementary skills the possibility to emerge and shifting firms' decisions towards investment in the production and adoption of innovative technologies.

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Table 1: OLS estimates of the effect of immigrants on patents' applications

	(1)	(2)	(3)	*benchmark* (4)	(5)
share of immigrants	0.364***	0.107***	0.093***	-0.017	
	(0.024)	(0.020)	(0.021)	(0.019)	
population diversity (ELF)					-0.933
					(1.020)
RD expenditures (% GDP)[(a)]			1.071***	1.034***	1.033***
			(0.397)	(0.391)	(0.390)
share VA agriculture			-0.119***	-0.032**	-0.032**
			(0.014)	(0.015)	(0.015)
share VA services			-0.021***	-0.064***	-0.064***
			(0.004)	(0.006)	(0.006)
share VA construction			-0.126***	-0.021	-0.021
			(0.028)	(0.025)	(0.025)
log pop 2001				0.277***	0.277***
				(0.051)	(0.051)
active age pop share 2001				0.056**	0.056**
				(0.024)	(0.024)
% of graduates on pop 18-64				0.191***	0.191***
				(0.019)	(0.019)
Year fixed effects	No	Yes	Yes	Yes	Yes
Region (NUTS-2) fixed effects	No	Yes	Yes	Yes	Yes
N. observations	607	607	607	607	607
R-squared	.46	.76	.80	.85	.85

*** significant at 1%; ** significant at 5%; * significant at 10%.

Note. The dependent variable is log patents' applications per 1000 inhabitants at the province (NUTS-3) level for Italy, 2003-2008. When not differently specified all independent variables are lagged one year. Standard errors are clustered at the *region* $\times$ *year* level because of the inclusion of an 'aggregated' variable (Moulton 1990) and robust to heteroskedasticity. Diversity of immigrants is measured using the ELF index (Mauro 1995).
[(a)] only available at the NUTS-2 level.

Table 2: 2SLS estimates of the effect of immigrants on patents' applications

	(1)	(2)
Second stage		
share of immigrants	-0.064**	
	(0.031)	
population diversity (ELF)		-3.457**
		(1.693)
RD expenditures (% GDP)[(a)]	0.944**	0.942**
	(0.378)	(0.378)
share VA agriculture	-0.025*	-0.025*
	(0.014)	(0.014)
share VA services	-0.069***	-0.069***
	(0.007)	(0.007)
share VA constructions	-0.022	-0.022
	(0.025)	(0.025)
log pop 2001	0.316***	0.317***
	(0.050)	(0.050)
active age pop share 2001	0.055**	0.055**
	(0.024)	(0.024)
% of graduates on pop 18-64	0.199***	0.199***
	(0.019)	(0.019)
First stage		
predicted share of immigrants	0.375***	
	(0.028)	
predicted population diversity		0.374***
		(0.029)
F-test excluded instrument	181.76	170.56
N. observations	607	607
R-squared	.37	.37

*** significant at 1%; ** significant at 5%; * significant at 10%.

Note. The dependent variable is log patents' applications per 1000 inhabitants at the province (NUTS-3) level for Italy, 2003-2008. When not differently specified all independent variables are lagged one year. All models include year and region (NUTS-2) fixed effects. Standard errors are clustered at the *region* $\times$ *year* level because of the inclusion of an 'aggregated' variable (Moulton 1990) and are robust to heteroskedasticity. Diversity of immigrants is measured using the ELF index (Mauro 1995).
[(a)] only available at the NUTS-2 level.

Table 3: OLS and IV estimates by skill level (1)

	OLS	2SLS 1st stage: high skilled	2SLS 1st stage: low skilled	2SLS 2nd stage
share of immigrants: high skilled[(b)]	-0.079			0.025
	(0.055)			(0.102)
share of immigrants: low skilled	-0.001			-0.094***
	(0.023)			(0.036)
RD expenditures (% GDP)[(a)]	0.998**	-0.355	-0.908*	0.988**
	(0.384)	(0.314)	(0.546)	(0.391)
share VA agriculture	-0.027*	0.061***	0.037*	-0.031**
	(0.016)	(0.010)	(0.022)	(0.015)
share VA services	-0.061***	0.013***	-0.081***	-.073***
	(0.007)	(0.005)	(0.011)	(0.008)
share VA construction	-0.015	0.044**	-0.093*	-0.031
	(0.026)	(0.018)	(0.048)	(0.026)
log population (2001)	0.281***	0.099**	0.193**	0.313***
	(0.052)	(0.039)	(0.095)	(0.051)
15-65 population share (2001)	0.058**	0.038***	0.142***	0.052**
	(0.025)	(0.014)	(0.047)	(0.023)
% of graduates on pop 18-64 (2001)	0.194***	0.022	-0.045**	0.195***
	(0.020)	(0.013)	(0.020)	(0.020)
predicted share of immigrants: high skilled[(c)]		0.337***	-0.213***	
		(0.032)	(0.049)	
predicted share of immigrants: low skilled		-0.027	0.528***	
		(0.020)	(0.028)	
Year fixed effects	yes	yes	yes	yes
Region (NUTS-2) fixed effects	yes	yes	yes	yes
F-test (1st stage)		57.78	176.88	
N. obs.	607	607	607	607
R^2	0.846	0.409	0.467	0.364

*** significant at 1%; ** significant at 5%; * significant at 10%.

Note. The dependent variable is log patents' applications per 1,000 inhabitants at the province (NUTS-3) level for Italy, 2003-2008. When not differently specified all independent variables are lagged one year. All models include year and region (NUTS-2) fixed effects. Standard errors are clustered at the *region* $\times$ *year* level because of the inclusion of an 'aggregated' variable (Moulton 1990) and are robust to heteroskedasticity.

[(a)] only available at the NUTS-2 level.

[(b)] the skill level is assigned to immigrants according to their country of origin: all immigrants from a country whose share of high-medium skilled emigrants on total emigrants to Italy in 2001 (Docquier-Marfoukof database) is larger than 0.56 (median value) are considered as high skilled.

[(c)] for the construction of the instruments the year of reference is 1991 (Docquier-Marfoukof database).

Table 4: OLS and IV estimates by skill level (2)

		2SLS		
	OLS	1st stage: high skilled	1st stage: low skilled	2nd stage
share of immigrants: high skilled[(b)]	0.001			0.113
	(0.083)			(0.154)
share of immigrants: low skilled	-0.029			-0.186**
	(0.053)			(0.091)
RD expenditures (% GDP)[(a)]	1.041***	-0.617*	-0.688	1.010**
	(0.389)	(0.356)	(0.433)	(0.394)
share VA agriculture	-0.033**	0.062***	0.027	-0.033**
	(0.016)	(0.013)	(0.017)	(0.015)
share VA services	-0.064***	-0.017***	-0.049***	-.073***
	(0.007)	(0.006)	(0.008)	(0.007)
share VA construction	0.002	-0.008	-0.053	-0.027
	(0.026)	(0.024)	(0.034)	(0.026)
log population (2001)	0.275***	0.159***	0.105	0.304***
	(0.052)	(0.041)	(0.066)	(0.053)
15-65 population share (2001)	0.056**	0.069***	0.104***	0.053**
	(0.024)	(0.016)	(0.032)	(0.024)
% of graduates on pop 18-64 (2001)	0.190***	-0.016	-0.020	0.190***
	(0.020)	(0.014)	(0.014)	(0.020)
predicted share of immigrants: high skilled[(c)]		0.163***	-0.401***	
		(0.055)	(0.063)	
predicted share of immigrants: low skilled		0.145***	0.742***	
		(0.044)	(0.051)	
Year fixed effects	yes	yes	yes	yes
Region (NUTS-2) fixed effects	yes	yes	yes	yes
F-test (1st stage)		70.63	165.81	
N. obs.	607	607	607	607
R^2	0.846	0.429	0.462	0.368

*** significant at 1%; ** significant at 5%; * significant at 10%.

Note. The dependent variable is log patents' applications per 1,000 inhabitants at the province (NUTS-3) level for Italy, 2003-2008. When not differently specified all independent variables are lagged one year. All models include year and region (NUTS-2) fixed effects. Standard errors are clustered at the *region* $\times$ *year* level because of the inclusion of an 'aggregated' variable (Moulton 1990) and are robust to heteroskedasticity.
[(a)] only available at the NUTS-2 level.
[(b)] for each province, the total number of immigrants from a given country is splitted by skill level according to the shares of high-medium skilled and low skilled emigrants on total emigrants from that country to Italy in 2001 (Docquier-Marfoukof database).
[(c)] for the construction of the instruments the year of reference is 1991 (Docquier-Marfoukof database).