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ABSTRACT

The Effect of (Mostly Unskilled) Immigration on the Innovation of Italian Regions*

We use small Italian regions (i.e. provinces) to investigate the causal effect of foreign immigration on innovation during 2003-2008. Using instrumental variables estimation (based on immigrants' enclaves), we find that the overall stock of immigrants did not have any effect on innovation. However, decomposing the overall effect into the contributions of low- and high-skilled migrants shows that an increase of 1 percentage point in the share of low-skilled migrants on the population reduces patent applications by about 0.2%. By contrast, the impact of high-skilled immigrants on innovation is positive, in line with the previous literature, but cannot be precisely estimated.

JEL Classification: O3, J2

Keywords: immigration, innovation, patent applications, regions, Italy

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1 Introduction

Immigration has recently been at the centre of the political and economic agenda. Economists have studied extensively the impact of immigration on several 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 Trindade 2002, Peri and Requena-Silvente 2010) and crime (Bianchi et al. 2012, Bell et al. 2013), just to take a few examples. The effect of immigration on innovation and technical change is instead much less studied. Yet innovation is a key factor for a country's economic growth (Romer 1990, Aghion and Howitt 1992, Acemoglu 2002, Jones 2002).

The existing work on the effect of immigrants on innovation is generally limited to the role played by highly educated immigrants, generally immigrants with at least tertiary education, and is mostly focused on the US. Chellaraj et al. (2008) found for the US a positive effect of skilled immigration and foreign graduate students on patent applications and grants. The share of skilled immigrants results to be beneficial for US invention also in the work of Hunt and Gauthier-Loiselle (2010). Kerr and Lincoln (2010) analyzed how the change in H-1B working population influenced ethnic patenting in US cities during the period 1995-2008: according to their estimates, total invention increased with higher admissions of high-skilled immigrants primarily through the direct contribution of Chinese and Indian inventors. Moser et al. (2011) found a positive effect of German Jewish *émigrés* scientists on US patenting during the period 1920-1970 (changes in patenting are examined at the level of research fields, rather than locations). Similar findings are reported in Stuen et al. (2012), who analyzed American Science&Engineering departments from 1973 to 1998 and found the effect of foreign doctoral students on innovation measured by publications and citations to be positive and significant, though not significantly different from that of natives.

As we said, a common denominator of all these studies is the exclusive focus on high skilled immigration. Yet, although in anglosaxon countries skilled immigration is a sizeable phenomenon—according to the Docquier and Marfouk (2006) data the percentages of tertiary-educated immigrants were in 2001 40.3% for Australia, 58.8% for Canada, 34.9% for the UK, ad 42.7% for the US— this is much less the case in European countries, for which just a few minority of immigrants is skilled. Just to take a few figures, according to the same source, the percentages of tertiary-educated immigrants were 16.4% for France, 21.8% for Germany, 15.4% for Italy and 18.5% for Spain. Now, although the existing literature has emphasized why there are good reasons to expect positive effects of skilled immigrants on the innovation of the receiving countries, it has much less to say about the general effect of immigrants, or of low-educated immigrants. Few papers have investigated the effect of low skilled immigration on innovation, and again they did it for the US. Lewis (2011), focusing on US metro areas and Mexican immigrants, found 'that plants added technology more slowly between 1988 and 1993 where immigration induced the ratio of high school dropouts to graduates to grow more quickly' (p. 1031) and that the increases in the relative supply of low-skill workers were associated with slower growth in capital-labour and capital-output ratios. Peri (2012) also focused on US states and Mexican immigration, and found that immigration promoted the adoption of unskilled-efficient technologies. For Europe, the only existing study is—to the best of our knowledge—Suedekum et al. (2012), which investigated, however, the separate effects of low and high-skilled immigrants not on innovation but on natives' wages and employment. Their analysis by skill level shows that the two groups of immigrants affect productivity (proxied by wages) in opposite directions: the authors observed 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.

In this paper, we make an attempt to partly fill the gap concerning the effects of overall immigration on innovation, and in particular of low-skilled immigrants, existing in the literature. In addition to providing evidence for a country which was exposed to a very fast and large wave of immigration during the 2000s—Italy–, and for which evidence is scant, we also use a very small geographical scale of analysis—Italian provinces corresponding to NUTS-3 regions[1]—, 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 to increasing the innovation potential of a region. More importantly, unlike most papers in the literature which only investigated the effect of skilled immigration, (i) we first focus on the general impact of immigration on innovation, and then (ii) separately look at the effects of low-educated and high-educated immigrants on innovation. Last but not least, we tackle potential endogeneity issues by using a well established instrumental variables (IVs, hereafter) strategy based on immigrants' *enclaves*.

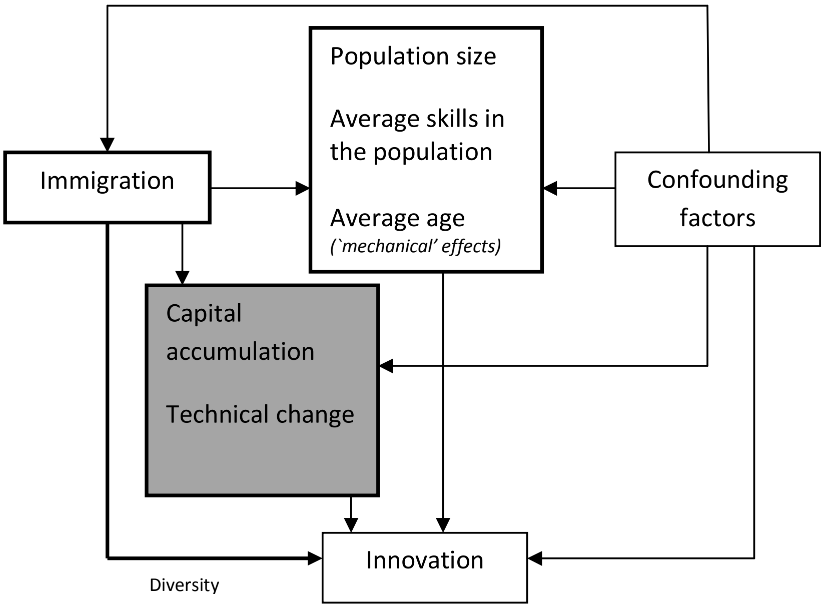
The structure of the paper is as follows. Section 2 sets the conceptual framework for our analysis. Section 3 describes the Italian context and the main features of Italy's immigration, and Section 4 the data used in the empirical analysis. The main results on the effect of immigration on patent applications 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, and Section 5.4 presents some robustness checks. The last section summarizes our main findings, and concludes.

2 Immigration and innovation: 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 raise 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 immigrants' levels of human capital compared to those of natives. Both population size and human capital levels are powerful predictors of innovation. Population size 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, Cowan and Zinovyeva 2013) an important engine for the production of new ideas. 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, since we expect younger individuals to be relatively

[1] NUTS stands for Eurostat Nomenclature of territorial units for statistics.

Figure 1: Conceptual framework: Effect of immigrants on innovation



more creative and innovative.[2] 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 behaviors, we expect their effect to be relevant both in the short and medium run and in the long run.

One aspect of immigration on which many papers 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 exchanges between culturally diverse individuals (Jacobs 1969). Highly skilled immigrants may also carry over their superior knowledge available in their origin countries, by spurring the diffusion of technology in the receiving countries (Hornung 2014). 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 immigrants in Italy), reduce social capital, and act as an obstacle to innovation and growth (see, for instance, Alesina and La Ferrara 2005). Positive effects on innovation are expected mainly by diversity in the skilled population, and many studies have focused accordingly only on skilled immigration.

There are other mechanisms through which one may expect negative effects of immigration on innovation. A large inflow of low-skilled immigrants in a region may affect firms' choices concerning technology adoption and investments in physical capital. (Lewis 2011, Peri 2012). This effect is likely to operate especially in the medium and long run. On the ground of this recent evidence, we will not focus only on skilled immigration, but we will consider in our study both the effect of overall immigration and the effects of skilled and unskilled immigrants separately.

[2]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).

Hence, when investigating the causal effect of immigration on innovation there are many potential pathways to be considered, some of which have effects of opposite sign. 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 require 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 capture *confounding factors*. This happens, for instance, 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 modeling approach to assessing the causal effect of immigration on innovation is to omit *mediating factors* (i.e. post-treatment variables) from the regression, 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 which 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 size 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 goods, and the stock of low skilled workers in the region through immigrants' inflows (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}), as

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

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 size, i.e. the potential mediating and confounding factor;[3] and u^{y}_{it} an error term. The share of immigrants is modelled as

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

where z_{it} is a variable which enters the immigrants' share equation only, i.e. the 'excluded instrument', and u^{imm}_{it} is an error term. Population size enters in this equation as immigrants may settle in large cities, which offer better employment opportunities. In this case, if $\lambda_3 \neq 0$ population size is a potential *confounding factor* in equation (1) and should be controlled for. Indeed, its exclusion from equation (1) will induce the researcher to attribute part of the effect of pop_{it} to imm_{it}. Moreover, if u^{y}_{it} and u^{imm}_{it} are correlated, perhaps owing to the omission of a third variable which affects both innovation and immigration, then the share of immigrants is endogenous with respect to innovation. Let us now model population as

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

where c_{it} is a factor affecting population size, and excluded from the previous two equations, and u^{pop}_{it} is an error term. Imm_{it} enters this equation as immigrants' inflows will affect the size

[3] For exemplificative purposes, we consider in the equation only one variable possessing these characteristics, although several others will be included in the empirical analysis.

of the population. If $\alpha_1 \neq 0$, then population is a *mediating factor* for the effect of immigrants on innovation.

What are the modeling alternatives available to 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 equation (1), 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 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}. In this case, IVs produce consistent estimates only if the excluded instrument z_{it} is not correlated with u^y_{it}. In any case, also in this best-case scenario, using the 'gross-effect approach' the specific effects of imm_{it} and pop_{it} in equation (1) 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 main equation [equation (1)] 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 so is to try to control for time-invariant or very time-persistent confounding 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, i.e. on the idea of immigrant *enclaves*. The main concern with this instrument is that also in 1995 immigrants may have located in provinces with characteristics correlated with a higher (or lower) future innovative potential (i.e., non-random past location), e.g., population size, violating the instrument's exogeneity assumption. This issue will be further discussed in section 5.4. As we already stressed, our approach partly differs from that adopted by most researchers who included potential mediating factors (e.g., population, human capital levels) in the estimation equation and treated them as exogenous variables.[4]

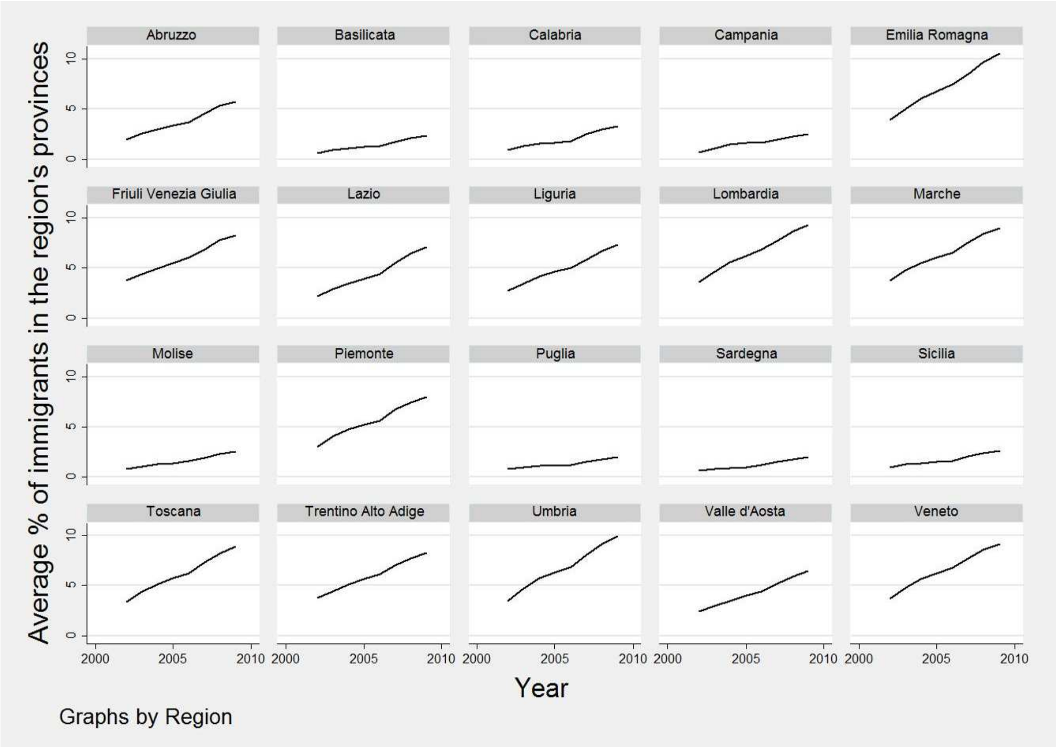
3 The country's context

Italy has been exposed to a very fast and large wave of immigration during the 2000s like many other European countries. The share of foreigners on the Italian population grew from 2.7% in 2003 to 5% in 2007.[5] High growth rates have been registered in Northern and Central Italy, while in the South the share of immigrants did not show fast changes (Figure 2). At

[4] In the estimated innovation equations, 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 regressions 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 main source of the information provided in this section is Fondazione Leone Moressa (2011).

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



Source: our data.
Note. Northern Italy: Emilia-Romagna, Friuli-Venezia Giulia, Liguria, Lombardia, Piemonte, Trentino-Alto Adige, Valle d'Aosta and Veneto; Central Italy: Lazio, Marche, Toscana and Umbria; Southern Italy and Islands: Abruzzo, Basilicata, Calabria, Campania, Molise, Puglia, Sardegna and Sicilia.

the beginning of 2007, foreigners accounted for 6.8% of population in Northern and Central regions, while they represented 1.6% of residents in Southern Italy. Not surprisingly, foreign people moving to Italy tend to settle in the richest regions and in big cities, which offer better opportunity of employment; 86.9% of immigrants were 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 Centre and the North of the country they exceed the level of 10%.[6]

Foreigners turn out to be an important resource for the Italian economy. In 2008 immigrants accounted for 12.1% of GDP formation; they were relatively young (32.6% of foreign employees was aged between 25 and 34, whereas for Italian employees the percentage was 20.9%) and represented 6.5% of entrepreneurs. However, the big majority of them tended to take manual-intensive and routine-type occupations (e.g., in construction, agriculture and personal-services sectors). One third of the low-skilled labour force was composed of immigrants (the share in the high -killed workforce was 1.9%); 37.7% of foreign workers were employed in low-skilled jobs (this percentage was 7.1% for Italian workers), 89.9% were blue collar workers. This is mainly due to low schooling levels that characterize most of foreign population in Italy, which fails to attract high-skilled workers and university students.[7]

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

[7]The top five countries by the number of immigrants in 2009 were Romania, Albania, Morocco, China and

Apart from the fact that immigrants in Italy are prevalently low skilled, the Italian context is peculiar also in another respect: highly 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 situation we just described is also 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 foreigners. To put it in other words, immigrants are affected by substantial over-education.

In brief, 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 immigrants play 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—2009. 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 the 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 database.[8] 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 of which they were part of.

As a proxy for innovative performance of Italian provinces we use the number of patent applications to the European Patents Office (EPO).[9] 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

Ukraine, accounting for about 50% of the total foreign-born population. According to Docquier and Marfouk (2006) 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 were 10% for Romania and Albania, 6% for Morocco and China, and 35% for Ukraine.

[8] 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 created four new provinces, that became operative in 2005. In 2004 the Italian Parliament approved three 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 do not affect our analysis.

[9] We use this information to build our dependent variable, that is the logarithm of patents' application per 1,000 inhabitants.

year are not included in the estimation. The EPO data used in this paper relate to all patent applications by priority year. The priority year refers to the first date the patent application was filed anywhere in the world. The OECD recommends using priority year as the closest to the actual timing of innovation. The distribution of patent 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 firm's 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 surrounding 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 innovation activities. Griliches (1990) highlights the limitations of using patents as a proxy of innovation: (i) not all innovations are patented,[10] thus patent data are only a partial indicator of innovative activity; (ii) not all patented innovations have the same level of quality;[11] (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 intrinsically 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).

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, which contains information on the stock of legal immigrants from 195 countries of origin resident in each province at the 31st of December. Although in this paper like in all the related literature we only focus on immigrants with legal status, Bianchi et al. (2012) considering the demands for regularization presented in 1995, 1998 and 2002 show that the distribution of regular and irregular immigrants were tightly related, and that the ratio of the two was very stable within provinces and (regularization) years. Here a clarification is in order. As mentioned before, in analyzing the effects of immigration on innovation an important aspect is the degree of diversity that immigrants bring to the community in which they decide to

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

[11] 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 (non negligible) time lag between applications and grants, an analysis of citations is unlikely to provide meaningful information on patents' quality.

settle. 'Cultural diversity' is what could affect positively (e.g., complementarities) or negatively (e.g., increased transaction costs) the efficiency of the local economy. 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.[12] However, Ottaviano and Peri (2006) show that, for the US, 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 the level of country of birth is also the reference point to construct the instruments for the 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 Systems of Territorial Indicators (*Sistemi Indicatori Territoriali*). We took data on the sectoral value added generated by each province (agriculture, services, manufacturing and construction) to construct the shares of valued added accounted for by each sector; this should allow us to control for the provinces' industrial structure and so for different propensities to patent across sectors. From the ISTAT databases come also the data we used to build the time-invariant (2001 values) control variables (resident population, working-age population and number of graduates).[13]

Finally, data on R&D expenditure as percentage of GDP are not available at the 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, we propose the following linear specification of the data generating process of patent applications

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

where i, j and t are province (NUTS-3), region (NUTS-2) and time subscripts, respectively and ε_{ijt} an error term. $\ln PATN_{it}$ are patent applications per 1,000 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; $\mathbf{X}_{it}$ 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);[14] $\mathbf{X}_{jt-1}$ includes the R&D intensity on regional GDP, which is not available at the

[12] Also the level of aggregation is often different. For example Bellini et al. (2013) use information about country of birth to aggregate immigrants in larger groups: EU countries, Africa, America, Asia, Oceania (and a residual 'unknown' group). Ozgen et al. (2012) operate a similar aggregation.

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

[14] 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

NUTS-3 level; $\mathbf{D}_{i2001}$ is a vector of covariates which may represent both mediating and confounding factors, and whose values have been included at a year pre-dating the estimation period (i.e., 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 span the years 2003—2008 (6 years), and has a panel structure. Since for some years information on patent applications is not available for all provinces, we have a unbalanced panel of 607 observations.[15] Time-variant regressors are lagged one period to make them predetermined with respect to the dependent variable. As in the regression we include some covariates which are more geographically aggregated with respect to the panel unit of analysis (i.e., $\mathbf{X}_{jt-1}$), the standard errors are clustered at the region by year level (Moulton 1990).

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 limited (especially in Sourthern provinces) time variation in this variable.[16] 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.[17] 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 accounted for by

et al. 1995)—which is in turn correlated with immigrants' employment opportunities and geographical location. These variables are included in the regressions as contemporaneous variables since the information is missing for 2002. The industrial structure might be affected by immigration, but this is likely to happen only in the long run (industrial structure is very persistent overtime); so endogeneity and reverse causality issues are unlike to arise for this variable in the short time span we consider. See, for instance, Card and Lewis (2007).

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

[16]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.

[17]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. Fixed-effects defined at the same level as the unit of analysis are instead used by the authors who consider Census data and a very long time span (see, for instance, Hunt and Gauthier-Loiselle 2010).

Table 1: OLS estimates of the effect of immigrants on patent 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	0.46	0.76	0.80	0.85	0.85

*** significant at 1%; ** significant at 5%; * significant at 10%.
[(a)] only available at the NUTS-2 level.
Note. The dependent variable is the logarithm of patent 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. Standard errors—in parentheses—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).

the share of immigrants in the province, and a simple OLS regression of the former on the latter returns an R-squared of 0.99.

Table 1 reports the OLS estimates. Column (1) shows the specification without control variables. A very significant positive correlation between the share of immigrants and patent applications emerges. Rising the share of immigrants by one percentage point (p.p., hereafter) is associated with a 0.36 percent increase in patent 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 of that in column (1) but still statistically significant, and the R-squared increases by 0.30, suggesting that a great deal of the variation in patent 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 on the coefficient of the immigrant share, confirming that immigrants' 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: the logarithm of population size, the share of active 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 patent 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 settle in highly populated provinces, in provinces with higher shares of active age population and of college graduates, provinces which could be *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.

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 share of immigrants. There may be several reasons why this assumption fails. It may happen that shocks to local demand, e.g. an increased foreign demand for a low-skilled good produced in the province, attract more immigrants locally and also have negative effects on innovation. Identification of the effect of immigrants requires therefore a presumably exogenous shock in the supply of immigrants at the province level. This shock does not necessarily need to be completely random, but must be 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. Immigrant networks may provide newly arrived individuals with important information on the local labour market and the availability of job vacancies, raising the returns to migration, or provide hospitality thereby reducing the costs of migration. 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 is built as follows. We take the yearly stock of immigrants by nationality in Italy as a whole (M_{gt}) and impute it to provinces (M_{git}) according to the distribution of nationalities across provinces in 1995 (θ_{gi1995}), computed using foreign residence permits data provided by the Italian Ministry of Interior.[18] In detail

$$\widehat{M}_{git} = \theta_{gi1995} M_{gt}. \tag{6}$$

We then aggregate 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 divide the latter by the predicted total

[18] Indeed, 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 (i.e., short-term stays) and who enter the country with a visa for reasons of visit, business, tourism and study do not require the issuance of a permit of stay.

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 do for immigrants, also the predicted total population $\widehat{POP}_{it}$ is 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[19] (see Ottaviano and Peri 2006):

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

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, between-province variation within the same region[20] in the distribution of immigrants by different nationality in 1995 was approximately random with respect to provinces' future innovation prospects. Some factors which could be responsible for very persisting differences in innovativeness across provinces are their industrial structure, the existence of agglomeration economies, or the levels of education in the population, which have been controlled for in our *benchmark* specification. Figure 3 shows that until 1995 for Italy as a whole 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. The same pattern is observed in figure 4 which plots the percentage of foreign residence permits on the population by region.

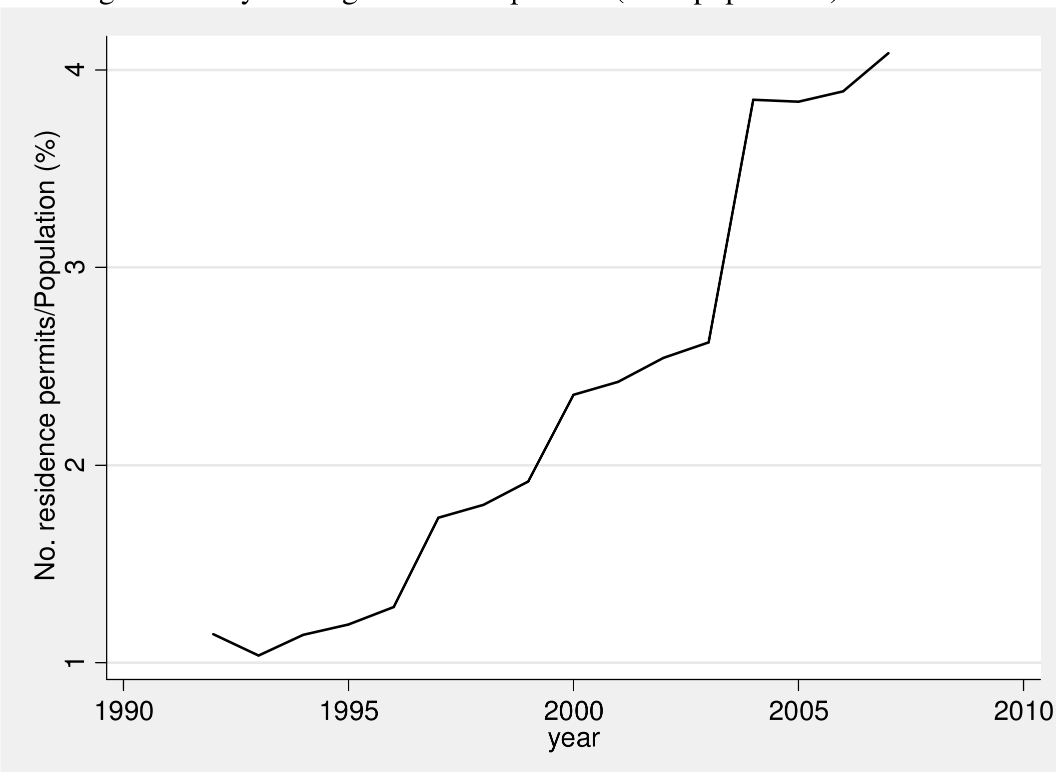
Table 2 reports the 2SLS results. In all cases we adopt the *benchmark* specification and cluster the standard errors at the region by time level. In column (1) we use the predicted share of immigrants. The F-test in the first stage is quite high at 181.76, confirming the strength of the excluded instrument (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' location choices. From the second stage we estimate that a one p.p. increase in the province's immigrant share reduces patent applications by 0.06 percent. In column (2), we use the ELF index as the dependent variable. 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 patent 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 patent applications. This finding is likely to be the result of the characteristics of Italian immigration which, as we outlined in Section 3, is prevalently unskilled. For this reason, in the following section we try to investigate the separate effects on innovation of high-skilled and low-skilled immigrants. Since the results using the immigrant

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

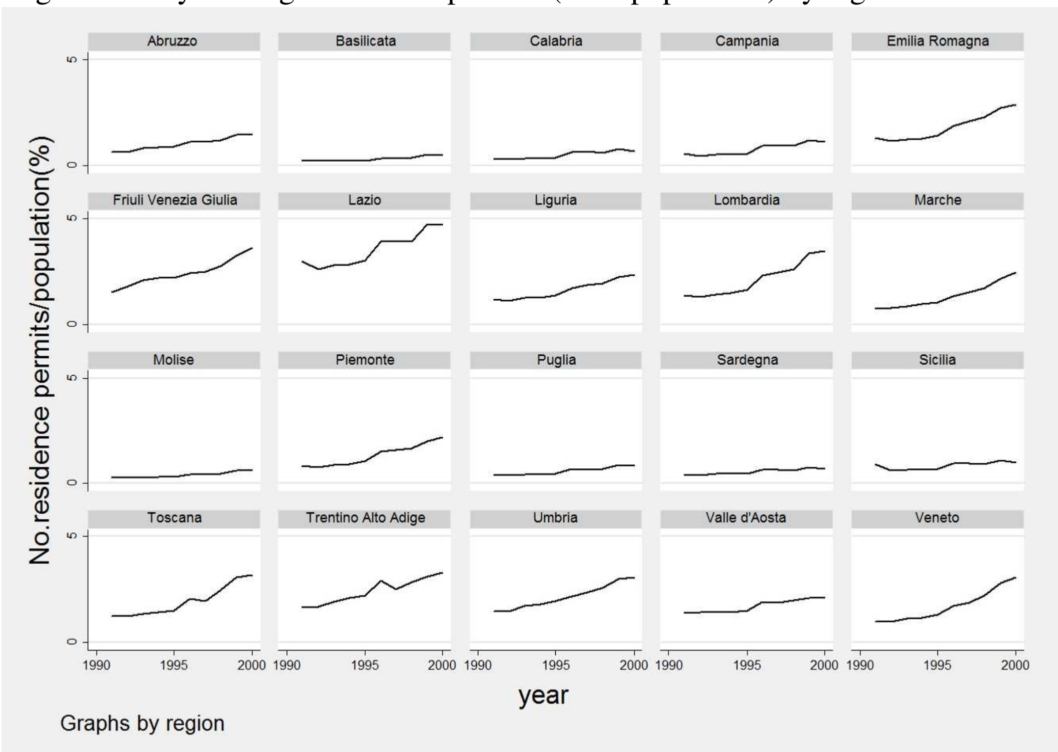
[20] Since we control for region fixed effects.

Figure 3: Italy: Foreign residence permits (% of population) 1992-2007



Source: ISTAT.

Figure 4: Italy: Foreign residence permits (% of population) by region 1991-2000



Source: ISTAT.
Note. Northern Italy: Emilia-Romagna, Friuli-Venezia Giulia, Liguria, Lombardia, Piemonte, Trentino-Alto Adige, Valle d'Aosta and Veneto; Central Italy: Lazio, Marche, Toscana and Umbria; Southern Italy and Islands: Abruzzo, Basilicata, Calabria, Campania, Molise, Puglia, Sardegna and Sicilia.

share and population diversity are very consistent, from now on we will focus only on regressions using the former as the dependent variable. 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.

5.3 Differences by immigrants' skill levels

The 2SLS results in the previous section suggest that the 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 immigrants as a whole, while previous papers, 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 finding of an overall negative effect may hide more complex dynamics related to the large heterogeneity in immigrants' skill levels, which can generate different effects, working in opposite directions. For this reason, in the current section we try to disentangle 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 components. 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 have to rely on external data and some simplifying assumptions. We use the dataset provided by Docquier and Marfouk (2006), 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. High-skilled migrants are those with at least tertiary educational attainment wherever they completed their schooling (i.e., 13 or more years of schooling); medium-skilled immigrants are those with upper secondary education (9-12 years of schooling); and low-skilled immigrants are those with primary or lower secondary education (less than 9 years of education). We take the data regarding 2001, which have less missing values, to compute for each country of origin the share of medium and high skilled emigrants on total emigrants to Italy. We refer to the share of medium and high skilled immigrants to obtain information about the immigrants which we define as 'high skilled'. This is justified by the fact that in 2002 in Italy more than 50% of the adult population (aged 20-64) still had lower than upper secondary education (OECD Education at a Glance 2005 — Tables).[21] The total number of immigrants from a given country is split by skill level according to the shares of high/medium skilled and low skilled emigrants on total emigrants in 2001. Since the skill structure provided by Docquier and Marfouk is time-invariant and province-invariant (data are available only for Italy as a whole), the time and geographical variation in the stocks of skilled and unskilled immigrants in our data come from the different dynamic of overall immigration by country of origin.[22] To build the instrumental variable $\widehat{MIGsh}_{it}$ for the two groups, high skilled and low skilled, we start from the 'predicted number of immigrants' in a province

[21] http://www.oecd.org/edu/skills-beyond-school/educationataglance2005-tables.htm

[22] A similar, but less precise, procedure to measure skilled and unskilled immigrants was used by Ozgen et al. (2012) who grouped migrants on the basis of the average skill level of the 'global region' from which they were from (Africa, Asia, America, Europe and Oceania). We consider here a finer classification using individuals' countries of origin.

Table 2: 2SLS estimates of the effect of immigrants on patent applications

	(1)		(2)	
	1st stage	2nd stage	1st stage	2nd stage
share of immigrants		-0.064**		
		(0.031)		
population diversity (ELF)				-3.457**
				(1.693)
RD expenditures (% GDP)[(a)]	-0.988	0.944**	-0.019	0.942**
	(0.747)	(0.378)	(0.014)	(0.378)
share VA agriculture	0.086***	-0.025*	0.002***	-0.025*
	(0.031)	(0.014)	(0.001)	(0.014)
share VA services	-0.073***	-0.069***	-0.001***	-0.069**
	(0.013)	(0.007)	(0.000)	(0.007)
share VA construction	-0.068	-0.022	-0.001	-0.021
	(0.056)	(0.025)	(0.001)	(0.025)
log population (2001)	0.297***	0.316***	0.005***	0.317***
	(0.107)	(0.050)	(0.002)	(0.050)
active age pop share (2001)	0.159***	0.055**	0.003***	0.055**
	(0.047)	(0.024)	(0.001)	(0.024)
% of graduates on pop 18-64 (2001)	-0.028	0.199***	-0.000	0.199***
	(0.025)	(0.019)	(0.000)	(0.019)
predicted share of immigrants	0.376***			
	(0.028)			
predicted population diversity			0.374***	
			(0.029)	
Year fixed effects	yes	yes	yes	yes
Region (NUTS-2) fixed effects	yes	yes	yes	yes
F-test excluded instruments (1st stage)	181.76		170.56	
F-test weak-instrument-robust[(b)]		3.87		3.85
(Anderson-Rubin Wald test)		[0.052]		[0.052]
N. obs.	607	607	607	607
R^2	0.42	0.37	0.43	0.37

*** significant at 1%; ** significant at 5%; * significant at 10%.
[(a)] only available at the NUTS-2 level. [(b)] p-value in brackets.
Note. The dependent variable is the logaritm of patent 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—in parentheses—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).

from a given country, obtained using the 'shift and share' method described in section 5.2. We then apply to the 'predicted number of immigrants' the procedure described above, in this case using data for 1991 in the Docquier-Marfouk database, and get the 'predicted high-skilled immigrants' by nationality. Summing this latter variable 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 estimate 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 in Table 3. OLS estimates of the coefficients of the lagged share of high-skilled and low-skilled immigrants, are not statistically significant. The sign of the coefficient on the share of low-skilled immigrants is negative, while the sign of the coefficient on the share of high-skilled immigrants is positive but very close to zero.

As for the 2SLS estimates, results from the first stage confirm also in this case the strength of the instruments: the F-tests take values 70.63 and 165.81 for high-skilled and low-skilled immigrants, respectively. The excluded instruments are highly significant. The difference in the magnitude of the values of the F-tests for the first-stage regressions for low-skilled and high-skilled immigrants and the significant negative sign on 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 and Salomone (2013). They show that networks favour 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 favour 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 of the share of low-skilled immigrants. Beine and Salomone 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.[23] In the second stage, the coefficient on the share of low-skilled immigrants is negative and significant: a rise in the share of low-skilled immigrants of one p.p. generates a reduction in patent applications of 0.19 percent. The coefficient on the share of high-skilled immigrants is positive but statistically insignificant; it suggests an increase in patent applications of 0.11 percent 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 overall consistent with the analysis of Lewis (2011) and Peri (2012). 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 are the two sides of the same coin, and can be explained by the particular features of the immigration phenomenon in Italy, characterized by the large prevalence of low-educated immigrants and the under-utilization of immigrants' human capital.

[23] A potential implication is that if the effect of immigrants is heterogeneous, the 2SLS estimates using the *enclave* instrument mainly capture the effect of compliers (local average treatment effects), that is of the highly-educated immigrants who followed early comers' location choices.

Table 3: OLS and 2SLS estimates by skill level

		2SLS		
	OLS	1st stage: HS	1st stage: LS	2nd stage
share of immigrants: HS[(a)]	0.001			0.113
	(0.083)			(0.154)
share of immigrants: LS	-0.029			-0.186**
	(0.053)			(0.091)
RD expenditures (% GDP)[(b)]	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***	-0.073***
	(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)
active age pop 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: HS		0.163***	-0.401***	
		(0.055)	(0.063)	
predicted share of immigrants: LS		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 excluded instruments (1st stage)		70.63	165.81	
F-test weak-instrument-robust[(c)]				4.01
(Anderson-Rubin Wald test)				[0.021]
N. obs.	607	607	607	607
R^2	0.85	0.43	0.46	0.37

*** significant at 1%; ** significant at 5%; * significant at 10%.
[(a)] for each province, the total number of immigrants from a given country is split 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-Marfouk database). [(b)] only available at the NUTS-2 level. [(c)] p-value in brackets.
Note. The dependent variable is the logarithm of patent 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—in parentheses—are clustered at the *region* × *year* level because of the inclusion of an 'aggregated' variable (Moulton 1990) and are robust to heteroskedasticity. HS and LS stand for high skilled and low skilled, respectively.

Table 4: 2SLS estimates - Robustness checks

	(1)		(2)		
	1st stage	2nd stage	1st stage: HS	1st stage: LS	2nd stage
share of immigrants		-0.033			
		(0.034)			
		(0.021)[e]			
share of immigrants: HS[a]					0.199
					(0.154)
					(0.144)[e]
share of immigrants: LS					-0.198**
					(0.086)
					(0.069)[e]
RD expenditures (% GDP)[b]	-0.978	0.987***	-0.613*	-0.692	1.071***
	(0.750)	(0.377)	(0.356)	(0.439)	(0.394)
share VA agriculture	0.085***	-0.023	0.063***	0.025	-0.034**
	(0.031)	(0.014)	(0.013)	(0.017)	(0.015)
share VA services	-0.078***	-0.057***	-0.015***	-0.058***	-0.063***
	(0.015)	(0.008)	(0.005)	(0.010)	(0.009)
share VA construction	-0.078	-0.016	-0.010	-0.064*	-0.025
	(0.059)	(0.025)	(0.025)	(0.036)	(0.026)
log population (2001)	0.322***	0.299***	0.163***	0.131**	0.287***
	(0.106)	(0.050)	(0.040)	(0.064)	(.053)
active age pop share (2001)	0.163***	0.054**	0.070***	0.107***	0.053**
	(0.047)	(0.024)	(0.016)	(0.031)	(0.024)
% of graduates on pop 18-64 (2001)	-0.013	0.164***	0.012	0.009	0.158***
	(0.033)	(0.023)	(0.016)	(0.020)	(0.024)
Patent applications in 1995[c]	-1.731	2.573***	0.200	-2.687**	2.210***
	(1.723)	(0.840)	(0.855)	(1.054)	(0.830)
predicted share of immigrants	0.373***				
	(0.031)				
predicted share of immigrants: HS			0.163***	-0.428	
			(0.057)	(0.067)	
predicted share of immigrants: LS			0.149***	0.752***	
			(0.044)	(0.051)	
Year fixed effects	yes	yes	yes	yes	yes
Region (NUTS-2) fixed effects	yes	yes	yes	yes	yes
F-test excluded instruments (1st stage)	141.99		65.42	151.64	
F-test weak-instrument-robust[d]		0.88			3.18
(Anderson-Rubin Wald test)		[0.349]			[0.045]
N. obs.	603	603	603	603	603
R^2	0.43	0.40	0.43	0.47	0.39

*** significant at 1%; ** significant at 5%; * significant at 10%.
[a] for each province, the total number of immigrants from a given country is split 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-Marfouk database). [b] only available at the NUTS-2 level. [c] per 1,000 inhabitants. [d] p-value in brackets. [e] standard errors robust to spatial correlation (Driscoll and Kraay 1998).
Note. The dependent variable is the logarithm of patent 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. Model (1) includes the share of immigrants as a whole, whereas in Model (2) immigrants are split according to their assigned skill level. 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. HS and LS stand for high skilled and low skilled, respectively.

5.4 Potential threats to identification

As we already said, given the short time span covered by our data, we did not include in the estimated equation province fixed effects, but only region fixed effects. This may pose a threat to our identification strategy. Indeed, one crucial assumption for our instrument (the predicted stock of immigrants) to be valid is that the past location of immigrants, i.e. the location in the base year (1995) was exogenous with respect to innovation during the period 2003—2008. A case in which this assumption may fail is when there is persistence in the patent innovations data generating process. In this case, the stock of immigrants in 1995 may be (either positively or negatively) correlated with a province's innovative potential, which in turn affects the province's innovation outcomes more than seven years later. In order to tackle this potential issue we re-estimated the 2SLS models in tables 2 and 3 adding as an additional control variable the province's patent applications back in 1995. The main goal is to exploit as an instrument only the variation in the predicted stock of immigrants which is not correlated with the province's lagged innovation performance (in 1995). The results are reported in Table 4. Column (1) shows that innovation in 1995 has a significant positive effect on innovation more than 7 years later, and that including this additional control the total stock of immigrants ceases to be statistically significant. This result seems to suggest that (conditional on the observables) immigrants negatively self selected in provinces with a low innovative performance, and that by omitting this control the immigrants' share was just capturing the effect of a lower innovative potential on current innovation. Column (2) shows that this is indeed the case. While the location of highly educated immigrants does not seem to be affected by patent applications in 1995, the contrary is true for lowly educated immigrants, which were prevalently located in relatively less innovative provinces. In the specification in which the separate shares of immigrants by skill are included, the positive coefficient on highly educated immigrants increases in magnitude with respect to the last column of Table 3 but remains statistically insignificant, while the coefficient on the stock of low educated immigrants is not affected by the inclusion of patent applications in 1995 and very similar to that in Table 3. On the ground of this last evidence, we consider those in Table 4 as our preferred specifications.

Since we did not model the spatial structure of the data, standard errors in Table 4, and the previous tables, may be wrongly computed in case of spatial correlation in the error term. For this reason, we also estimated our preferred specifications computing standard errors which are robust in the presence of very general forms of cross sectional correlation using the procedure suggested in Driscoll and Kraay (1998). These standard errors are included in Table 4 and clearly show that the statistical significance of our coefficients of interest does not fall.

6 Concluding remarks

In this paper, we investigate the effect of the share of immigrants in the population and of the population diversity (enhanced by immigration) on Italian provinces' patent applications (per 1,000 inhabitants), as a proxy for innovation performance. The potential endogeneity of immigration is tackled by employing a well established procedure in the literature, based on immigrants' *enclaves*.

Differently from most work in this literature, we do not limit our 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 dictated by the consideration that, in addition to possible positive effects on the production of new ideas arising from skills' complementarities, recent empirical contributions have suggested that there may also be adverse effects on innovation generated by the inflow of foreign population (Lewis 2011, Peri 2012). 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 labour force, may all act as obstacles to innovation and growth. We show that this is likely to be the case for Italy, which mostly attracts low-skilled immigrants who are employed in traditional sectors and for which 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 preferred econometric specification suggests that as far as total immigration is concerned, there was no significant effect on innovation during 2003—2008.

Investigating the separate effects on innovation of high skilled and low-skilled immigrants, we show that 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 of about 0.2%. The fact that the impact of high-skilled immigrants turns out to be positive but not significant can be explained by the particular features of immigration in Italy. We have seen that not only Italy mainly attracts unskilled immigrants, but also that the few high-skilled immigrants moving to Italy 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.

Our results stress the key importance of both immigration policies and labour market policies to promote the pro-innovation effect of immigrant. The former should be aimed at attracting high-skilled immigrants and the latter at ensuring a good match between immigrant workers' skill levels and the working positions they fill. Improving these policies should allow Italy to exploit the innovative potential embodied in skilled foreigners, as other countries do. Also, given the short period spanned by our data, all the effects we estimated should be interpreted as medium-run/short-run effects, while considering longer periods additional effects on the economy may emerge (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 further adapts its technological choices to the availability of a large share of unskilled workforce. A better use of the competences of skilled immigrants and the valorisation of their human capital could help to compensate the discussed negative effects, by attracting educated immigrants, giving complementary skills the possibility to emerge, and shifting firms' decisions towards investments in the production and adoption of innovative technologies.

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