The Effect of Immigration on Provinces' and Firms' Innovation in Italy

Massimiliano Bratti and Chiara Conti

June 13, 2016

Abstract

This paper investigates the effect of immigration on innovation in Italy, a country characterized by prevalently unskilled immigration and large job ethnicization. Both provinces' innovation measured by patent applications, and firms' self-reported innovations are analyzed. The estimated effect of a one percentage point increase in the share of immigrants on per capita patent applications ranges between -0.08 and -0.05 percent, depending on the way zeros in patent applications are dealt with. In contrast, our analysis does not show any effect of the share of immigrants when a broader measure of firm innovation, encompassing both radical and incremental innovations, is considered.

JEL classification. O3 · J2

Keywords. immigration · innovation · patents · provinces · firms · Italy

1 Introduction

Immigration has recently been at the centre of the political and economic agenda. Economists have studied extensively the impact of immigration on host countries, for instance on 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. More recently, a growing number of studies have also started to investigate the effect of immigrants on innovation. Innovation is indeed a key factor for a country's economic growth (Romer 1990, Aghion and Howitt 1992, Acemoglu 2002, Jones 2002), and another important channel through which immigration can impact on the performance of the receiving economy.

There are several mechanisms through which immigrants could affect innovation. They are well summarized in Ozgen et al. (2013). On the positive side, immigrants may be positively self-selected (Borjas 1987) in terms of intelligence, creativity, risk propensity, entrepreneurship, and other characteristics which are positively related to innovativeness; immigrants are generally younger than natives, and this may affect their productivity and creativity (Lindh and Malmberg 1999, Feyrer 2008); immigrants are more mobile, and workers' mobility is an important source of knowledge spillovers between firms and regions (Faggian and McCann 2009, Simonen and McCann 2010); a sustained inflow of immigrants increases the size of the population, which 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); immigrants are culturally different, and this may increase productivity and innovation in case workers with different cultural backgrounds are complementary in production (Ottaviano and Peri 2006, Suedekum et al. 2014, Parrotta et al. 2014); when immigrants' are highly educated, they may change substantially the local stock of human capital, which is in turn related to productivity and the production of new ideas (Moretti 2004, Sanroma and Ramos 2007, Andersson et al. 2009, Cowan and Zinovyeva 2013). These positive effects are of course more likely to be induced by high-skilled immigration.

Much less attention has been paid to the potentially negative effects of immigration on innovation. Cultural and language differences raise communication costs; reduce trust, cooperation, and social capital; and increase social conflict (Alesina and La Ferrara 2005), which might negatively affect many economic outcomes, including innovation. Moreover, while the positive effects of skilled immigrants on the hosting economies are generally undisputed (see Section 2), the channels through which low skilled immigrants may impact either positively or

negatively an economy have been much less investigated. A high inflow of low-educated immigrants, for instance, may make cheap labour force available in traditional sectors, potentially increasing their relative size (Card and Lewis 2007, De Arcangelis et al. 2015), with negative effects on innovation. An abundant low-skilled labour force may reduce firms' incentives to invest in skill-intensive production technologies, hampering innovation and physical capital investments (Lewis 2011, Peri 2012).

This brief overview of the potential channels of influence of immigrants on innovation already suggests that since high-skilled and low-skilled immigrants may have opposite effects on innovation, focusing exclusively on the former is likely to give only a very partial picture of the overall impact of migration on the receiving country's innovation performance.

In spite of this, the existing research is generally limited to the role played by highly educated immigrants, i.e. often individuals with tertiary education, and is mostly focused on the U.S. (see Section 2). Yet, most immigrants are low skilled, even in the U.S., and although in English speaking countries skilled immigration is a sizable 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 U.S.—this is much less the case in most European countries, for which just the minority of immigrants are skilled.[1] Just to give a few figures, according to Docquier and Marfouk (2006), in 2001 the percentage of tertiary-educated immigrants was 16.4% in France, 21.8% in Germany, 15.4% in Italy, and 18.5% in Spain.

This paper contributes to the existing literature in at least two ways. Firstly, not limiting the analysis to high-skilled immigrants but also exploring the effects of overall and low-skilled migration on innovation. Evidence is provided for a country, Italy, which was exposed to a very fast and large wave of immigration, mostly low-educated and coming from developing countries, during the 2000s. The Italian case and our analysis are likely to be informative also for other countries, given the recent migration trends. Indeed, political instability and extensive warfare causing disruption of national educational systems and of the economic and social life in large areas of North Africa and the Middle East are likely to feed substantial waves of young

and low-educated immigrants in the next years, increasing the share of low skilled immigrants in E.U. countries' populations (LaBanca 2016).

Secondly, evidence is provided not only for radical but also for incremental innovation. Radical innovations, proxied by patent applications, are investigated using a very small geographical scale of analysis: Italian provinces (*province*), corresponding to Nomenclature of Territorial Units for Statistics (NUTS)-3 regions — which, compared to larger areas, enables us to better control for differences in institutional and socio-economic factors which are difficult to observe and which may simultaneously contribute to both attracting new immigrants and to increasing the innovation potential of a region. Moreover, since there are several forms of innovation, some of which are just incremental or less formal than patenting, the effect of the local share of immigrants on firms' self-reported innovation outcomes (product, process and organizational innovations) is also studied, using survey data. This is important in countries like Italy in which formal R&D expenditure is low, and an important share of innovations has informal sources. Last but not least, potential endogeneity issues are tackled using a well established instrumental variables (IVs, hereafter) strategy based on immigrants' *enclaves*.

Our analysis shows that....

The structure of the present paper is as follows. Section 2 briefly summarizes the recent literature on the effects of immigrants on innovation. Section 3 describes the Italian context and the main features of Italy's immigration, and Section 5 the data used in the empirical analysis. Our empirical strategy and identification are discussed in Section 4. The main results on the effect of immigration on provinces' patent applications and firms' self-reported innovations are commented on in Section 6. The last section summarizes our main findings and draws some conclusions.

2 Literature review

This section describes the main findings of papers which have investigated the effect of immigrants on innovation. For reasons of space, our review cannot be exhaustive, and just fo-

cuses on some recent contributions, which can be grouped into regional-level, firm-level, and individual-level studies. A recent survey on the impact of immigration on innovation can be found in Jensen (2014).

Regional-level studies. Most studies take a regional approach and investigate the effect of the local presence of skilled immigrants on innovation, generally proxied by patents. Hunt and Gauthier-Loiselle (2010) using both a panel of U.S. states and individual-level data, find important positive effects of immigrant college and post-college graduates, and immigrant scientists and engineers on patenting per capita. Since the aggregate estimates of the effect of skilled immigrants appear to be larger in magnitude than the individual-level estimates, the authors conclude that there are substantial spillover effects on natives' patenting. Kerr and Lincoln (2010) analyze how the change in H-1B working population influences ethnic patenting in U.S. cities during the period 1995–2008: 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 few papers investigating European countries also mainly focus on skilled immigration. Niebuhr (2010) investigates the effect of ethnic diversity of R&D employees and high-skilled R&D employees on the innovation of German regions. Diversity turns out to be positively associated with patenting, but the association loses statistical significance when regional fixed-effects are controlled for. Gagliardi (2015) combines Community Innovation Survey data with Labour Force Survey data to build a panel for British local labour market areas. This approach enables the author to include in the empirical analysis a large number of control variables compared to other regional studies, and to focus on self-reported innovation measures, which are not normally available in regional data. Her findings support the evidence of a statistically significant positive causal effect of immigration on process innovation at regional level. Bosetti et al. (2015) focus on the effect of migrants employed in skilled professions in 20 European countries and report positive effects both on the number of patent applications and the number of citations to published articles.

Other studies did not use geographical-level data but time-series data (Chellaraj et al. 2008), or data aggregated at the research field (Moser et al. 2014) or university department level (Stuen

et al. 2012), but always maintaining the main focus on skilled migration, and demonstrating that migrant scientists and foreign graduate students raise innovation.

Much fewer studies have investigated the impact of *unskilled* immigrants on innovation. Lewis (2011), focusing on U.S. metro areas and Mexican immigrants, document that plants add technology more slowly where immigration induces the ratio of high school dropouts to graduates to grow more quickly, and that increases in the relative supply of low-skilled workers are associated with slower growth in capital–labour and capital–output ratios. Peri (2012) also focuses on U.S. states and Mexican immigration, and finds that immigration promotes the adoption of unskilled-efficient technologies. From this limited evidence, it seems that unskilled migration may reduce innovation and firms' adoption of unskilled labour saving technologies. As for Europe, there is, to the best of our knowledge, no study which explicitly assesses the effect of low-skilled immigration on innovation. Ozgen et al. (2012) uses NUTS-2 European regions to estimate the effects of the share of immigrants by continent of origin (Africa, America, Asia, Central Europe, Other European countries) on innovation, showing some heterogeneity, which can only be indirectly related, however, to the skill levels of the immigrants. Suedekum et al. (2014) investigate the separate effects of low- and high-skilled immigrants not on innovation but on natives' wages and employment in German labour markets. Their analysis shows that the two groups of immigrants affect productivity (proxied by wages) in opposite directions: significant positive effects are observed only when immigrants are highly skilled, while the effect of the share of low-skilled immigrants is negative and drives the overall effect of immigration.

Firm-level studies. Very few studies have adopted a firm-level approach. Maré et al. (2014) combines data from New Zealand's Longitudinal Business Database with Census data on workforce composition at the Labour Market Area level to investigate the impact of the local share of foreign immigrants, high-skilled workers, and new arrivals on a range of innovation outcomes provided by survey data (process innovation, product innovation, organizational and management innovations, marketing innovations, etc.). The authors do not find an independent effect of local labour force characteristics on innovation after controlling for firm size, indus-

try, and expenditures on research and development. These results are at odds with the evidence in Gagliardi (2015), which uses similar measures of innovation derived from survey data, although they could be explained by the fact that Maré et al. (2014) include in the regressions the share of foreign immigrants without distinguishing by skill level. A different approach is followed by Parrotta et al. (2014), who use Danish employer–employee linked data, matched with European Patent Office (EPO, hereafter) data, and mainly focus on workers' *ethnic diversity within the firm*, finding that it may facilitate firms' patenting activity by increasing the propensity to patent innovations, increasing the overall number of patent applications, and by enlarging the breadth of patenting technological fields, conditional on patenting. Ozgen et al. (2013) investigates the effect of a firm's share of immigrant workers (without distinguishing by skill level) and employees' ethnic diversity on innovation, finding a negative effect of the former and a positive effect of the latter on product innovation. Therefore, unlike with the regional-level studies, the findings from firm-level studies are much more mixed.

Individual-level studies. Another strand of the literature uses individual-level data to assess the productivity and innovativeness of immigrants. Hunt (2011) finds, using the 2003 U.S. National Survey of College Graduates, that immigrants who entered on a student/trainee visa or a temporary work visa had a large advantage over natives in wages, patenting, and publishing. This advantage is mainly explained by immigrants' higher educational achievements, and fields of study. Franzoni et al. (2014) use an international dataset for scientists active in research to assess performance (impact factor, total citations) differentials associated with geographic mobility. The authors find evidence that migrant scientists perform better than those who have not experienced international mobility and that this is not explained by positive self-selection.

3 Immigration in Italy

Italy has been exposed to a very fast and large wave of immigration during the 2000s, like many other European countries. The average share of foreigners in the population grew from 2.4% in 2002 to 7.6% in 2010 (our computation on data obtained from the ISTAT Demographic portal).

High growth rates have been recorded by Northern and Central Italy, while in the South the share of immigrants did not show rapid changes. In 2010, foreigners accounted for 10% of the population in the North-West, 10.4% in the North-East, 9.7% in the Centre, 3.1% in the South, and 2.7% in the Islands. Not surprisingly, foreigners moving to Italy tend to settle in the richest regions and in big cities, which offer better employment opportunities: in 2010, 23% of Italy's immigrants lived in Lombardy, and 12% in Lazio. The provinces of Milan and Rome alone accounted for 18% of total immigrants.

Compared to other countries, Italy is mostly characterized by young and low-skilled immigrants (Del Boca and Venturini 2005). The top five countries by number of immigrants in 2010 were Romania, Albania, Morocco, China and Ukraine, accounting for about 50% of the total foreign-born population in Italy. According to Docquier and Marfouk (2006) database, for those nationalities in 2001 the shares of high-skilled immigrants (those having completed tertiary education) in total immigrants to Italy were 10% for Romania and Albania, 6% for Morocco and China, and 35% for Ukraine (source: ISTAT Demographic portal). However, given the generally quite low educational attainment of the native population, immigrants turned out to be on average slightly more educated than natives in Italy. According to OECD (2012), in 2010 the percentage of the Italian population with tertiary education in the age group 25-64 was 15%, the same as in Portugal and two percentage points higher than in Turkey (the country with the lowest educational attainment in the OECD), against an OECD average of 31% and a EU21 average of 28%.

The microdata of the 2001 Italian Population Census allows us to look at the average educational levels of natives and immigrants in Italy. Considering the population in the age group 25-64, the percentages of migrants (natives) with less than upper secondary, upper secondary and tertiary education were 52.6% (57.2%), 32% (32%) and 15.4% (10.8%), respectively. Data for the 2010 Italian Labour Force Survey (ISTAT) shows that about 10 years later the average educational attainment in the 25-64 age group was increasing, and that, also thanks to the Bologna process that reformed the European higher education system, now natives have a higher educational achievement than migrants. The percentages of the foreign (native) popula-

tion with less than upper secondary, upper secondary and tertiary education are 45.8% (45.1%), 42.6% (39.8%) and 11.6 (15.1%), respectively.

Besides immigrants in Italy being mostly low skilled, the Italian context is peculiar also in another respect: highly educated immigrants often take up low-skilled jobs. It has been shown that, given similar characteristics (in terms of sex, age, education, and experience), foreigners were three times more likely to fill low-skilled positions in 2008. 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 make up 40% of the workers in low-skilled personal services and 18% of the workers in the construction sector (Fondazione Leone Moressa 2011). This phenomenon has been called 'job ethnicization', and is related to a substantial overeducation of immigrants in Italy. Immigrants' overeducation is not a peculiar feature of the Italian economy though. Nieto et al. (2013), for instance, find strong evidence of overeducation in Europe, especially for non-EU immigrants. Previous studies show that this leads to considerably lower returns to both education and labour market experience for migrants than for natives, and to low labour market assimilation of foreign workers (Venturini and Villosio 2008, Dell'Aringa et al. 2015). The 2010 Italian Labour Force Survey (ISTAT) shows that the first three sectors of employment for migrants were Household Services (25.5%), Construction (16.7%) and Manufacturing (19.1%), while natives were prevalently employed in Manufacturing (19.4%), Education, Health and other Social services (15.5%) and Wholesale and Retail Trade (15%). As for the distribution of immigrants by job qualification, 1.3% were legislators, managers or entrepreneurs, 2.2% worked in intellectual professions, 4% in technical professions, and 1.9% were white-collar workers. By contrast, 13.7% were skilled independent workers, 28.2% were artisans, specialized blue collar workers and skilled workers in agriculture, 10.4% were semi-skilled blue collar workers, and the large majority, 38.3%, worked in unskilled professions.

All in all, from these figures it emerges that in Italy immigrants mainly appear as a source of low-skilled and cheap labour, which is employed in traditional (i.e., low value-added) economic sectors. The few highly educated immigrants settling in Italy take up low skill jobs and are generally overeducated. However, on average they are not less educated than natives, owing to

the low educational attainment of the latter. As we will see later, all these facts together explain the role that immigrants play in Italy's innovation.

4 Empirical strategy and identification

We use province-level data in order to assess the impact of immigration on radical innovation, measured by patent applications. Then we conduct a similar analysis using survey data containing firms' self-reported information on innovation outcomes to account for forms of innovation that are just incremental or less formal than patenting. This also allows us to address some of the objections related to the use of patent data (see next section).

4.1 Province-level analysis

A provincial knowledge production function (KPF) in which the share of immigrants in the population appears among the inputs (see, for instance, Hunt and Gauthier-Loiselle 2010) is estimated.

$$\ln PATN_{ijt} = \alpha_0 + \delta_t + \delta_j + \alpha_1 MIGsh_{it-1} + \alpha_2 \mathbf{X}_{it-1} + \alpha_3 \mathbf{D}_{i2001} + u_{ijt} \tag{1}$$

Here, i, j and t are province (NUTS-3), region (NUTS-2), and time subscripts, respectively. u_{ijt} is an error term and αs and δs the parameters to be estimated. The dependent variable — $\ln PATN_{it}$ — is the logarithm of the number of patent applications per 1,000 inhabitants. In order to retain zeros in province-time observations, 0.001 was added to the number of patents before taking the logarithm. All time-variant regressors are lagged one period to make them predetermined with respect to the dependent variable. $MIGsh_{it-1}$ is the (lagged) share of immigrants in the population; in the specification distinguishing by immigrants' skill level, this regressor is replaced by $MIGHsh_{it-1}$ and $MIGLsh_{it-1}$, which stand for the shares of high-skilled and low-skilled individuals, respectively. $\mathbf{X}_{it-1}$ is a vector of control variables accounting for the level of R&D effort (a standard input in KPF) and provinces' industrial

structure. The main rationale for including these latter variables 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. $\mathbf{D}_{i2001}$ is a vector of covariates that may represent both mediating and confounding factors in our analysis, and whose values have been included at a year predating the estimation period (i.e. 2001, our dataset spanning the period 2002-2010): the logarithm of population size, the share of active age population, and the college share in the population, as a proxy of human capital. All these variables are expected to have a positive effect on innovation (see the Introduction). Considering these variables, which are potentially affected by migration, in 2001 ensures that they are not affected by migration flows during our estimation period, i.e. they are not 'bad controls' (Angrist and Pischke 2009). The terms δ_t and δ_j are year and region (NUTS-2) fixed-effects. Worth noting is that because of the short time interval spanned by our data, province fixed effects are not included in the specification (1). $MIGsh_{it}$ is quite persistent over time, and the within estimator would use only limited (especially in Southern provinces) time variation in this variable (see Figure 1 in Appendix). This problem is emphasized, for instance, in Niebuhr (2010), who did not stress the results of the fixed effects model because of the very low time variation in her data, and the potentially large attenuation bias caused by measurement error. An intermediate approach is used instead, and NUTS-2 fixed effects are included in the analysis. This enables us not only to use time variation but also *cross-sectional variation between provinces within the same region*. NUTS-2 fixed-effects, in turn, enable catching all potential time-invariant unobserved differences existing across Italian regions, which are likely to be important especially because of the strongly persistent North–South economic divide. A similar approach is used, for instance, by Wagner et al. (2002) and Bratti et al. (2011), in their analyses of the effect of immigration on trade. Fixed effects defined at the same level as the unit of analysis are instead included by authors using Census data and a very long time span (see, for instance, Hunt and Gauthier-Loiselle 2010).

4.2 Firm-level analysis

A specification similar to (1) is employed to estimate firms' KPFs, which are used to assess the impact of the local share of migrants ($MIGsh_{it-1}$) on firms' innovation. The main difference is that now the dependent variables are dichotomous indicators for firms' self-reporting having introduced product, process and organizational innovations in the last three years,

$$INN_{kit,t+3} = \alpha_0 + \delta_t + \delta_j + \delta_s + \alpha_1 MIGsh_{it} + \alpha_2 \mathbf{X}_{kt} + \alpha_3 \mathbf{D}_{i2001} + u_{kit,t+3} \tag{2}$$

where k, i, j, s and $t, t+3$ (i.e. a three-year period) are firm, province (NUTS-3), region (NUTS-2), sector and time subscripts, respectively, and u_{kit} an error term. δ_t and δ_j are time and region fixed effects, respectively, while δ_s stands for 2-digit industry fixed effects. Variables which have been found to affect innovation at the firm level by previous studies (Maré et al. 2014, Gagliardi 2015) are included among the firm-level covariates $\mathbf{X}_{kt}$: firm size (in logs), capital intensity, the share of workers with a university degree, and the ratio of R&D expenditure to total revenue. $\mathbf{D}_{i2001}$ is the vector of province time-invariant covariates described above.

4.3 Identification

OLS give consistent estimates only if, conditional on the observables included in the innovation equation, the error term of Equations (1)and (2) are uncorrelated with the share of immigrants. There are several reasons why this assumption may fail. Shocks to local demand, e.g., an increased foreign demand for a product locally manufactured, could attract more immigrants and also have positive effects on innovation. Identification of the effect of immigrants requires, therefore, a presumably exogenous source of variation in the local supply of immigrants at the province level which can be used in the application of the IVs estimator. This variation need not be completely random, but must be uncorrelated with the unobserved innovation capacity of a province (or a firm). To build an 'instrument' for the share of immigrants, the procedure proposed in Altonji and Card (1991) is followed. This strategy has been already extensively

employed in the empirical literature on immigration (see, for some recent applications, Hunt and Gauthier-Loiselle 2010, Lewis 2011, Peri 2012, Gagliardi 2015). Identification is based on immigrant *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 immigration, or provide hospitality, thereby reducing the costs of immigration. Although $MIGsh_{it}$ refers to the total share of immigrants in the population, separate information by country of origin is available for the whole stock of migrants in each year of our sample. In more detail, our instrument is built as follows. The yearly stock of immigrants in Italy from country g as a whole (M_{gt}) is imputed to provinces (M_{git}) according to the distribution of nationalities across provinces in 1995 (θ_{gi1995}). Formally,

$$\widehat{M}_{git} = \theta_{gi1995} M_{gt}. \tag{3}$$

All immigrants' predicted stocks by nationality ($\widehat{M}_{git}$) are aggregated at the province level to compute the total stock of immigrants in province i at time t, and then divided by the predicted total provincial population, obtaining in this way the instrument, i.e., the predicted immigrants' share ($\widehat{MIGsh}_{it} = (\sum_{g=1}^{G_{i1995}} \widehat{M}_{git})/\widehat{POP}_{it}$). As is done for immigrants, also the predicted total population $\widehat{POP}_{it}$ is computed apportioning to provinces the population in each year according to the 1995 provincial distribution of residence permits. This avoids the denominator of the ratio being endogenous, as it includes the stock of migrants. The instrument has two components. The first is the total stock of individuals by nationality in Italy, which should be uncorrelated with a single province's supply and demand shocks impacting on local innovation. The second component is the distribution of immigrants in 1995. The latter should be uncorrelated with *unobserved factors* affecting patenting more than 7 years later, conditional on the observables included in the regressions. The main identifying assumption is that, conditional on the observables, between-province variation within the same region 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 persistent 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 Equation (1). Moreover, Figure 3 in Appendix shows that until 1995, in Italy the percentage of foreign residence permits in the population was quite constant, and that 1995 predates the period of rapid inflow of immigrants into Italy. The same pattern is observed in Figure **??** in Appendix, which plots the amount of foreign residence permits as a percentage of the total population at the regional level (NUTS-2). This does not completely exclude, however, that some immigrants might have decided their location on the basis of unobserved variables that are correlated with current innovation, since the innovation process is quite persistent over time. Thus, to make the exogeneity assumption even more credible, the logarithm of provinces' per capita patent applications back in 1995 is included in the regressions. After the inclusion of this additional control, the only variation in immigrants' past locations which is used for identification is that which is uncorrelated with past provincial innovation. Past patent applications are also included in the regressions estimated with OLS for the sake of comparability.

A similar procedure was followed to build the instrumental variables for high-skilled and low-skilled immigrants.

5 Data description

In this section, we describe the main features and sources of the province-level and firm-level data used in our analysis.

5.1 Province-level data

The panel data used for the province-level analysis contains information on the demographic and economic indicators for 103 Italian provinces (NUTS-3 level) for 2002—2010[2], and represents a balanced panel of 927 observations.

Patents and innovation

The number of patent applications to the European Patents Office (EPO) is used as a measure of the innovative performance of Italian provinces. The data are retrieved from the OECD REGPAT database, July 2014, where the patent data have already been linked to regions by using the addresses of the applicants and inventors by the OECD. The regional breakdowns provided in REGPAT correspond to the latest version of NUTS-3. The OECD REGPAT database derives from two complementary sources of data: the *European Patent Offices Worldwide Statistical Patent Database* (PATSTAT, Spring 2014), and the OECD patent database that relies on *EPO's epoline database* (EPO Bibliographic Database and Abstracts – EBD), covering all publications up to the end of May 2014. Two main datasets are covered by REGPAT: (i) Patent applications filed with the EPO from 1977 to 2011, and (ii) Patent applications filed under the Patent Cooperation Treaty (PCT) at the international phase, from 1997 to 2011. All patent applications filed with the EPO from 2002 to 2010[3] with at least one Italian inventor are extracted from the database. Patent applications are collected by priority year, corresponding 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 time of the innovation. In this study, patent applications are assigned to provinces according to the inventor's province of residence. Using the residence of inventors rather than that of applicants (usually the firm's headquarters) prevents under-estimating the innovation activity of peripheral regions (Moreno et al. 2005) and makes it more likely that innovations, related to the characteristics of the surrounding geographical areas, are attributed to the regions where they have actually been produced. In the original database, a fractional count is used to allocate patents: if one application has more than one inventor, the application is divided equally among all of them and subsequently among their provinces of residence, thus avoiding multiple counting. It is well known that patent applications 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, thus patent data are only a partial indicator of innovative activity; (ii) not all patented innovations have the same level of quality; (iii) the 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 the procedures and standards between patent offices. Despite all the above mentioned limitations, patents continue to be considered one of the most reliable measures of innovation output, and are commonly used in empirical research. Moreover, applications to the 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 (Moreno et al. 2005). However, some of the objections related to the use of patent data will be addressed in our firm-level analysis, which investigates self-reported measures of innovation.

Figure 2 in Appendix shows how the number of patents per 1,000 inhabitants and the share of migrants have evolved at the national level from 2002 to 2010, which is our study period.

Immigrants and instrumental variables

As in Hunt and Gauthier-Loiselle (2010), the variable used in our analysis to assess the impact of immigration on innovation is the share of immigrants in the resident population. 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 (Italian National Statistics Institute), which contains information on the stock of legal immigrants from 187 countries of origin resident in each province at the 31st of December. Although this paper, as with all in the related literature, only focuses on immigrants with legal status, Bianchi et al. (2012), considering the demands for regularization presented in 1995, 1998 and 2002, showed that the distributions of regular and irregular immigrants were tightly related, and that the ratio of the two was very stable across provinces and (regularization) years. The evolution of the share of immigrants in the national population is shown in Figure 2 in Appendix.

Information on immigrants' country of origin is necessary to build the instrument based on immigrants' *enclaves*, described in the previous section. For each country of origin, the yearly stock of immigrants in Italy is imputed to provinces according to its distribution in 1995. Aggregating for each province across nationalities gives the 'predicted number of immigrants.' The distribution of nationalities across provinces in 1995 is computed using data about foreign

residence permits[4] provided by the Italian Ministry of Interior, since disaggregated data on resident by foreign nationality is only available for Italian provinces since 2002 through ISTAT. The choice of 1995 stems from the fact that in that year there were 103 provinces, while the number of provinces was 95 before. In this study, an attempt is made to provide some evidence regarding possible different effects of low-skilled and high-skilled immigrants on innovation, which might be concealed when looking at immigrants as a whole. Unfortunately, data from the demographic portal of ISTAT do not provide information on the skill level of immigrants (such as the level of education or occupation), so another source of data is needed to construct our variables on high-skilled and low-skilled immigrants. These variables are built starting from individual-level data collected in the *Labour Force Survey* (quarterly data), available at the Laboratory for Elementary Data Analysis (ADELE), through which ISTAT makes it possible to researchers to access the restricted use microdata files of all ISTAT surveys. For each individual observation, information about the status of immigrants (born abroad and with foreign citizenship) and the highest educational qualification are available. Using sample weights, the number of low-skilled and high-skilled immigrants at province level, and the relative shares on the population, are computed. High-skilled migrants are defined as those with at least upper secondary education. 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).[5] Regressions are also estimated including among the high-skilled migrants only those with tertiary education, and the main findings do not change (results are available upon request).

Istruments for the high-skill and low-skill migrant shares are computed using the dataset collected by Docquier and Marfouk (2006). In particular, the instrument for the high-skill and low-skill migrant shares are computed applying to the 'predicted shares of immigrants' the skill structure by country of origin in 1991. Indeed, Docquier and Marfouk (2006) provide the number of immigrants to Italy in 1991 from 195 countries, divided into low-, medium- and high-skilled. The authors count as immigrants all working-aged (25 and over) foreign-born individuals. Consistently with our definition of skilled migrants, medium- and high- skilled

migrants are pooled in the same category.

Control variables

Data from the *Labour Force Survey* — elementary data collapsed at province level using sample weights — are also used to create the control variables accounting for provinces' industrial structure and R&D effort. In particular information on individual sector of employment (ATECO 2-digit) is used to create a partition of the total employment in 15 sectors. The variable accounting for R&D effort is the percentage of individuals with occupations related to R&D activity (both in the public and the private sector) in the total employment. Weighted micro-census data (2001) are used to create the time-invariant provincial variables predating the estimation period (the logarithm of population size, the share of active age population, and the college share in the population in 2001).

The list of variables in the province-level dataset and sample summary statistics are presented in Table ??? and ??? in the Appendix, respectively.

5.2 Firm-level data

The data used for the firm-level analysis come from three firm-level surveys. In particular, data were pooled from the 2001–2003 and 2004–2006 waves of the Survey of Italian Manufacturing firms (SIMF), and the "European Firms in a Global Economy" survey (EFIGE) covering 2007–2009. SIMF (Capitalia 2002) is currently managed by the Unicredit banking group (formerly by Mediocredito and later by Capitalia). The survey collects information from a nationally representative sample of manufacturing firms with 11–500 employees and from all firms with more than 500 employees.[6] The dataset gathers a wealth of information on: balance sheet data integrated with information on the structure of the workforce and governance aspects; R&D expenditures and ICT; international activities (e.g., exports, FDI flows); and information on financial structure and strategies. The EFIGE (Altomonte and Aquilante 2012) survey gathers, for seven European countries, nationally representative data on manufacturing firms with more than 10 employees. The survey's questionnaire is mainly focused on 2008, with some questions on the firms' activities in 2009 and previous years. The original dataset includes 14,911 firms

located in seven countries and collects many information about the firms' international activities, innovation, organization, and workforce, which are complemented with balance sheet data from AMADEUS, a database of comparable financial information for public and private European companies collected by the Bureau van Dijk. In this paper, only the Italian sample of EFIGE is used. The structure of the EFIGE survey was designed in analogy with Unicredit's SIMF survey, which ensures high comparability of the two data sources. All surveys provide sample weights, which are used in the regression analysis.

Most important for our analysis, both SIMF and EFIGE asked firms whether they introduced innovations in products, processes, or organizational aspects, in the last three years, and the province in which firms were located (which is used to merge the firm-level surveys with the data on immigration and other control variables used in the province-level analysis).[7] As the innovation outcomes refer to three-year periods, firms in SIMF 2001–2003 and 2004–2006 are merged with the stocks of immigrants in 2002 (the first available year) and 2004, respectively, while EFIGE data is merged with the immigrant stock in 2007, i.e. we took the variable in the first year of each three-year period, with the exception of the first wave, for which data are only available since 2002. Pooling SIMF and EFIGE we obtain a pooled cross-section of 11,214 observations.

The list of variables in the firm-level dataset and sample summary statistics are presented in Table ??? and ??? in the Appendix, respectively

6 Main results

6.1 Province-level analysis

This section presents the results from the estimation of the impact of immigration on provinces' innovation as described in Equation (1). Table 1 shows the OLS estimates. Column (1) presents the specification without control variables. A very significant positive correlation between the share of immigrants and patent applications emerges. An increase in the share of immigrants by one percentage point (p.p., hereafter) is associated with a 0.3 percent increase in patent ap-

plications (per 1,000 inhabitants); however, provincial unobserved factors could be responsible for this correlation. In column (2), year and region fixed-effects are controlled for. The coefficient on the share of immigrants reduces sharply (0.08) but is still positive and statistically significant, and the R-squared increases by a noticeable 0.35, suggesting that a great deal of the variation in patent applications is accounted for by regional differences and time trends. In column (3), two important potential determinants of innovation, R&D intensity in GDP and the province's industrial structure, are added to the regressors. Inclusion of these further controls has little effect on the coefficient on the immigrant share, confirming that the latter is not very correlated with these direct determinants of innovation, at least in the relatively short time span considered. Column (4) presents the specification including 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. As anticipated, their confounding role could be isolated by including their values in 2001, i.e. before the estimation period, so that 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 changes in sign and is also greatly reduced in magnitude, falling to -0.022 (t=-1.7)). These results suggest that in the previous columns, immigrants' share was picking up the fact that immigrants settle in highly populated provinces, in provinces with higher shares of active age population and of college graduates, i.e. in provinces which could be *ex-ante* more innovative. In column (5), the logarithm of the number of patent applications (per 1,000 inhabitants) is added to the control variables to have a comparable specification with the IVs' estimates; its inclusion makes our identification more credible and allows for better controlling for province's industrial structure. With this additional control, the coefficient on the share of immigrants is still negative, but very small, and loses statistical significance. This last result suggests that immigrants tend to select into provinces where past innovation is low (negative self-selection). More evidence on this will be provided in the first stages of 2SLS.

All in all, the OLS results show that the stock of immigrants is likely to capture unobservable provincial characteristics that are positively correlated with innovation. After including a

large set of control variables, the correlation between immigrants and innovation disappears. Of course, we cannot exclude that the omission of other relevant variables could still make the effect of immigration appear more positive than it is in reality, and this represents the main reason for using IVs.

Finally, in column (6), an attempt is made to disentangle the effects on innovation of low-skilled and high-skilled immigrants. As was said in Section 5, our data do not contain information on the skill level of immigrants in each year (such as the level of education or occupation), so one has to rely on external data and some simplifying assumptions to apportion the total number of immigrants. Column (6) shows that OLS estimates of the coefficients on the share of high-skilled and low-skilled immigrants are not statistically different from zero.

Table 2 presents the IVs' results for the specification with the share of immigrants as a whole and for the specification in which immigrants are divided by skill level. Two-stage least squares (2SLS) were applied. In the specification with the share of all immigrants, the F-statistic for the excluded instrument in the first stage is high, at 225.31, confirming the strength of the predicted share of immigrants. The instrument's coefficient is highly significant and equal to 0.37 (t=15), suggesting that although immigrant enclaves contribute to explaining an immigrant's location, there are other factors which also affect an immigrant's residential choice. Interestingly enough, column (1) shows that immigrants tend to locate in provinces with less patents per capita in 1995. From the second stage, a one p.p. increase in the province's share of immigrants reduces patent applications by 0.05 percent (t=2). As for the regression by skill level, the results from the first stage confirm also in this case the strength of the instruments: the F-statistics are 89.34 and 235.75 for high-skilled and low-skilled immigrants, respectively. The difference in the magnitude of the values of the F-statistics for the two types of immigrants can be explained in light of the findings of Beine and Salomone (2013), who show that networks favor the immigration of less-skilled immigrants rather than skilled immigrants. Accordingly, immigrant enclaves are likely to be a better predictor of the share of low-skilled immigrants. The excluded instruments are highly statistically significant. Column (4) suggests that the origin of the negative correlation between the total share of immigrants and past patents per

capita observed in column (1) is the set of choices made by low-skilled immigrants as to their location. In the second stage, there is no significant effect of either high-skilled or low-skilled immigrants on patents. A potential caveat with these estimates is that the shares of high- and low-skilled immigrants are very highly correlated (the correlation coefficient is 0.93, significant at the 1% level), and this partly depends on the way they were built. For this reason, Table A.3 in the Appendix presents separate regressions including either low- or high-skilled immigrant shares. It must be kept in mind that each of the two regressions is likely to suffer from an omitted variables bias. In case the effect of low-skilled immigrants on innovation is negative and that of high-skilled immigrants is positive, indeed, an upwardly biased negative coefficient and a downwardly biased positive coefficient is expected in the models in columns (2) and (4), respectively. However, the coefficient on the share of high-skilled immigrants is -0.09 (t=-1.7) and that on low-skilled immigrants is -0.079 (t=2.2). These results are consistent with immigrants' negatively affecting patent applications in Italy, irrespective of their skill levels.[8]

These results suggest that, at least for Italy, in 2002–2009, immigration had an overall negative effect on innovation, when the latter is measured by patent applications. This finding is likely to be the result of the characteristics of Italian immigration which, as outlined in Section 3, is prevalently unskilled. Moreover, the (few) high-skilled immigrants moving to Italy are often employed in traditional sectors and fill low-skilled jobs. Nevertheless, the lack of significant effects for the shares of immigrants by skill level must be interpreted with caution. This finding could partly stem from the way in which the proxies for the shares of high-skilled and low-skilled immigrants, for which data are not directly available, were built. To build these proxies, information on the immigrants' educational attainments, provided in the dataset in Docquier and Marfouk (2006), was used. The skill structure refers to a time period earlier than our data, and is time-invariant and province-invariant, which could generate sizable measurement errors affecting the estimation results.

6.1.1 Zeros in patent applications

As was said in Section 4, observations with zero patent applications (some provinces did not file any patent applications in some years) were retained in the analysis by adding a small constant to the number of patents per capita before taking the logarithm. In spite of this procedure's being quite common in empirical research (see, for instance, the trade literature on gravity equations), Santos Silva and Tenreyro (2006) strongly advise against it and in favor of using quasi-Poisson modeling. Thus, this section checks the robustness of our results by estimating an 'instrumental variables' Poisson model. In case of a non-negative dependent variable (y), such as patent applications per capita, the outcome can be modeled as an exponential function $y = \exp(Xb)u$, where X are the covariates, b the coefficients to be estimated, and u an error term. The IV-Poisson model consists in solving the moment conditions $Z'(y - \exp(Xb)/\exp(Xb))) = Z'(y * \exp(-Xb) - 1)) = 0$ where Z are the instruments satisfying the condition $E(Z'u) = 0$.[9] Estimation of specifications equivalent to those in columns (1) and (2) of Table 2 returns a coefficient of -0.08 (t=-2.5) on the total share of immigrants, and of 0.03 (t=0.2) and -0.15 (t=-1.5) on the shares of high-skilled and low-skilled immigrants, respectively. Hence, the results from the IV-Poisson model qualitatively confirm those obtained using 2SLS, although the coefficient on the total share of immigrants is higher in magnitude and more precisely estimated.[10]

6.2 Firm-level analysis

This section presents the results using firm-level data. Due to the high number of outcomes considered (product, process and organizational innovation), only the Linear Probability Model (LPM) 2SLS results are presented.[11] Table 3 shows the second stages for all innovation outcomes, both for the total share of immigrants and the shares divided by skill, and some diagnostics on the instruments. The full first-stage results are presented in Table 4.

The instruments' diagnostics are generally good. The F-statistics for the excluded instruments are satisfactory, and do not show evidence of a weak instrument problem.

[Table 3 about here]

Columns (1)–(3) of Table 3 show the results for the total share of immigrants on product, process and organizational innovation, respectively. Self-reported innovation includes innovations in products, processes, and organizational forms which are new to the market, but also, and more often, those which are new only to the firm. Local immigrants do not seem to significantly affect the probability of introducing self-reported innovations. As for the impact of the other variables, firm size and R&D intensity are positively associated with all three forms of innovation, capital intensity is positively associated with process innovation only, and the college share especially with product and organizational innovations. In contrast, unlike in the regional-level analysis, province-level variables, including the past (1995) stock of patent applications per capita, are not significantly correlated with firms' self-reported innovations, confirming that patent applications and self-reported innovations are capturing very different aspects of firm innovativeness.

The results for the share of immigrants by skill level are shown in columns (4)–(6) of Table 3. The shares of low- and high-skilled immigrants are never significantly associated with self-reported innovation, although they have the expected sign, i.e. negative for the former and positive for the latter. The results for the other variables are very similar to those already noted for the previous columns. [12]

Our results are in line with Maré et al. (2014), which did not find any effect of immigration on self-reported innovation. Since according to Maré et al. a large part of the effects of immigrants is captured by the correlation with a firm's industry indicators, size, and R&D intensity, it is important to check whether the coefficients of immigrant shares become statistically significant when these covariates are omitted, but this was not found to be the case.[13] This is not very surprising for Italy, where many firms are small and very few firms engage in formal research and development activities.

Since innovation refers to three-year periods, a choice had to be made on which year of immigration data to select when merging firm and province data. Although in our opinion the best option would be to use the immigrant share before the first year spanned by each wave

of SIMF and EFIGE, this could not be done because of the unavailability of immigration data before 2002. The first year in each period was used instead for 2004–2006 and 2007–2009, while 2002 (the first year for which data are available) was chosen for 2001–2003. The results of our analysis are however robust to merging the firm data with the immigrant shares in the central year of each wave (i.e. 2002, 2005 and 2008, respectively).

7 Concluding remarks

This paper investigates the effect of the share of immigrants in the population both on Italian provinces' patent applications (per 1,000 inhabitants), and on firms' self-reported innovations, which, unlike the former, encompass both radical and incremental innovations, and is also a proxy of adoption as well as production of new knowledge. The potential endogeneity of immigration is tackled by employing a well established procedure in the literature, based on immigrant *enclaves*.

Unlike most work in this literature, our analysis is not limited to the effects of skilled immigration, but focuses on the general impact of immigration, and also makes an attempt at separating the effects on innovation of low-educated and high-educated immigrants. This choice was dictated by the consideration that, in addition to possible positive effects on the production of new ideas arising from complementarities of skills, 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 a lesser incentive for the adoption of new capital-intensive technologies owing to the abundance of cheap low-skilled labour, may all act as obstacles to innovation and growth. Our analysis shows that this is indeed 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 an increase by one percentage point in the share of immigrants

reduces patent applications by between 0.05 and 0.08 percent, depending on the way zeros in patents' applications are dealt with. In contrast, when using survey data and self-reported innovations, which also include those which are new to the firm and not necessarily to the market, immigration does not appear to affect firms' innovativeness.

The overall negative impact of immigrants on patented innovations can be explained by the particular features of immigration in Italy. Not only does Italy mainly attract unskilled immigrants, but also the few high-skilled immigrants who do move to Italy are often employed in traditional sectors and fill low-skilled jobs, suffering from substantial overeducation. So, due to the scarcity of educated immigrants and the 'waste' of their human capital, the (potentially) positive effect of high-skilled immigrants on innovation is not observed in Italy.

Our results stress the key importance of both immigration policies and labour market policies in promoting the pro-innovation effect of immigrants. 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 could 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 estimated effects should be interpreted as short/medium-run effects; when 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 unskilled and cheap workforce. A better use of the competences of skilled immigrants and the valorisation of their human capital could help ameliorate 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 advanced technologies.

Notes

[1] In what follows, the words skilled and highly educated are used interchangeably.

[2] The number of Italian provinces has changed in recent times: at present, there are 110 provinces in all. Prior to 2006, there were only 103. The original data were recorded according to 103 provinces only before 2006. Data from 2006 onwards were reclassified by us in order to have 103 units of observation for the whole time period: the values referring to the new provinces have been imputed to the provinces of which they were part.

[3]Data are still partial for 2011.

[4]A resident permit can be defined as the administrative act by which the alien who has lawfully entered the territory of the state is allowed to settle in Italy for a specific period. Foreigners who intend to stay in Italy for a period less than three months (i.e. short-term stays) or who enter the country with a visa for reason of visit, business, tourism or study do not require the issuance of a permit of stay.

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

[6] SIMF data have been already used to investigate issues related to firms' innovation. See, for instance, Benfratello et al. (2008), Alessandrini et al. (2010) and Bratti and Felice (2012), among others.

[7] Owing to the nature of the data, our firm-level analysis will only be able to shed light on the extensive margin of innovation, as information on the number of innovations was not collected.

[8] The results in this section are also robust to the inclusion of region by time interaction fixed effects, which are likely to better capture time-varying regional unobservables that might have been omitted from the analysis. Results available on request. In this case, R&D intensity is omitted from the model and standard errors are not clustered. For the specifications in Table 2, standard errors which are robust to the error term's being heteroskedastic, autocorrelated up to the second lag, and possibly correlated between provinces not necessarily in the same region, i.e. across space (Driscoll and Kraay 1998, Hoechle 2007) were also computed. They are generally lower than those presented in Table 2, namely 0.011 (t=-4.3) for the total share of immigrants, and 0.054 (t=-0.2) and 0.035 (t=-2.1) for high-skilled and low-skilled immigrants, respectively. However, the validity of Driscoll and Kraay standard errors may be questioned owing to the short time span covered by our study, and the low number of clusters.

[9] The model was estimated using the STATA command `ivpois`.

[10] The complete estimates are available upon request. Standard errors are bootstrapped (500 replications). As in the linear model with patent applications in logarithms, the coefficients can be interpreted as the percentage increase in patent applications per capita produced by a one p.p. increase in the share of immigrants.

[11] The OLS results are available upon request from the corresponding author.

[12] The immigrant shares continue to be statistically insignificant even when an IV-Probit model is used instead of the LPM. Full results available on request.

[13] The only significant (and positive) coefficient is that of high-skilled immigrants in the product innovation equation.

References

Acemoglu, D., 2002. Directed technical change. *Review of Economic Studies* 69, 781–809.

Acemoglu, D., Linn, J., 2004. Market size in innovation: Theory and evidence from the pharmaceutical industry. *The Quarterly Journal of Economics* 119, 1049–1090.

Aghion, P., Howitt, P., 1992. A model of growth through creative destruction. *Econometrica* 60, 323–351.

Alesina, A., La Ferrara, E., 2005. Ethnic diversity and economic performance. *Journal of Economic Literature* 43, 762–800.

Alessandrini, P., Presbitero, A. F., Zazzaro, A., 2010. Bank size or distance: what hampers innovation adoption by SMEs? *Journal of Economic Geography* 10, 845–881.

Altomonte, C., Aquilante, T., 2012. The EU-EFIGE/Bruegel-Unicredit dataset. Working Papers 753, Bruegel.

Altonji, J., Card, D., 1991. The effects of immigration on the labor market outcomes of less-skilled natives, in Abowd J. M. and Freeman R. B. (Eds) *Immigration, Trade and the Labor Market*, pp. 201–234, University of Chicago Press, Chicago.

Andersson, R., Quigley, J. M., Wilhelmsson, M., 2009. Urbanization, productivity, and innovation: evidence from investment in higher education. *Journal of Urban Economics* 66, 2–15.

Angrist, Joshua D., Jörn-Steffen Pischke, 2009. Mostly Harmless Econometrics: An Empiricist's Companion. Pricenton: Princeton University Press.

Becker, G. S., Glaeser, E. L., Murphy, K. M., 1999. Population and economic growth. *American Economic Review* 89, 145–149.

Beine, M., Salomone, S., 2013. Network effects in international migration: education versus gender. *The Scandinavian Journal of Economics* 115, 354–380.

Bell, B., Fasani, F., Machin, S., 2013. Crime and immigration: evidence from large immigrant waves. *The Review of Economics and Statistics* 95, 1278–1290.

Benfratello, L., Schiantarelli, F., Sembenelli, A., 2008. Banks and innovation: microeconometric evidence on Italian firms. *Journal of Financial Economics* 90, 197–217.

Bianchi, M., Buonanno, P., Pinotti, P., 2012. Do immigrants cause crime? *Journal of the European Economic Association* 10, 1318–1347.

Borjas, G. J., September 1987. Self-selection and the earnings of immigrants. *American Economic Review* 77, 531–53.

Borjas, G. J., 2003. The labor demand curve is downward sloping: reexamining the impact of immigration on the labor market. *The Quarterly Journal of Economics* 118, 1335–1374.

Borjas, G. J., 2005. The labor-market impact of high-skill immigration. *American Economic Review* 95, 56–60.

Bosetti, V., Cattaneo, C., Verdolini, E., 2015. Migration of skilled workers and innovation: a European Perspective, *Journal of International Economics* 96, 311–322.

Bratti, M., De Benedictis, L., Santoni, G., 2014. On the pro-trade effects of immigrants. *Review of World Economics* 150, 557–594.

Bratti, M., Felice, G., 2012. Are exporters more likely to introduce product innovations? *The World Economy* 35, 1559–1598.

Capitalia, December 2002. Ottavo rapporto sull'industria italiana e sulla politica industriale. Tech. rep., Capitalia, Rome.

Card, D., 2001. Immigrant inflows, native outflows, and the local labor market impacts of higher immigration. *Journal of Labor Economics* 19, 22–64.

Card, D., 2005. Is the new immigration really so bad? *The Economic Journal* 115, F300–F323.

Card, D., Lewis, E., 2007. The diffusion of Mexican immigrants during the 1990s: Explanations and impacts, in Borjas, G. J. (Ed.), *Mexican Immigration to the United States*, pp. 193–227. The University of Chicago Press, Chicago.

Chellaraj, G., Maskus, K. E., Mattoo, A., 2008. The contribution of international graduate students to US innovation. *Review of International Economics* 16, 444–462.

Cowan, R., Zinovyeva, N., 2013. University effect on regional innovation. *Research Policy* 42, 788–800.

De Arcangelis, G., Di Porto, E. Santoni, G., 2015. Migration, labor tasks and production structure, *Regional Science and Urban Economics*, 53, 156–169.

Del Boca, D. and Venturini, A. (2005). Italian migration. In K. Zimmermann (Ed.), *European Migration: What Do We Know?,* pp. 303–336. Oxford University Press.

Dell'Aringa, C., Lucifora, C. and Pagani, L. (2015). Earnings differentials between immigrants and natives: the role of occupational attainment. *IZA Journal of Migration* 4, 1–18.

Docquier, F., Marfouk, A., 2006. International migration by educational attainment (1990-2000), in Ozden, C., Schiff, M. (Eds.), *International Migration, Remittances and Development*. Palgrave Macmillan, New York.

Driscoll, J. C., Kraay, A. C., 1998. Consistent covariance matrix estimation with spatially dependent panel data. *The Review of Economics and Statistics* 80, 549–560.

Faggian, A., McCann, P., 2009. Human capital, graduate migration and innovation in British regions. *Cambridge Journal of Economics* 33, 317–333.

Feyrer, J., 2008. Aggregate evidence on the link between age structure and productivity. *Population and Development Review* 34, 78–99.

Fondazione Leone Moressa, 2011. *Rapporto annuale sull'economia dell'immigrazione. Edizione 2011*. Il Mulino, Bologna.

Franzoni, C., Scellato, G., Stephan, P., 2014. The mover's advantage: the superior performance of migrant scientists, *Economics Letters*, 122, 89–93.

Gagliardi, L., 2015. Does skilled migration foster innovative performance? Evidence from British local areas. *Papers in Regional Science*, 94, 773-794.

Glaeser, E. L., 1999. Learning in cities.*Journal of Urban Economics* 46, 254–277.

Gould, D. M., 1994. Immigrant links to the home country: empirical implications for U.S. bilateral trade flows. *The Review of Economics and Statistics* 76, 302–16.

Griliches, Z., 1990. Patent statistics as economic indicators: a survey. *Journal of Economic Literature* 28, 1661–1707.

Hoechle, D., 2007. Robust standard errors for panel regressions with cross-sectional dependence. *The Stata Journal* 7, 281–312.

Hunt, J., 2011. Which immigrants are most innovative and entrepreneurial? Distinctions by entry visa. *Journal of Labor Economics* 29, 417–457.

Hunt, J., Gauthier-Loiselle, M., 2010. How much does immigration boost innovation? *American Economic Journal: Macroeconomics* 2, 31–56.

Jensen, P. H., 2014. Understanding the impact of migration on innovation. *Australian Economic Review* 47, 240–250.

Jones, C., 2002. Sources of U.S. economic growth in a world of ideas. *American Economic Review* 92, 220–239.

Kerr, W. R., Lincoln, W. F., 2010. The supply side of innovation: H-1b visa reforms and U.S. ethnic invention. *Journal of Labor Economics* 28, 473–508.

Klevorick, A. K., Levin, R. C., Nelson, R. R., Winter, S. G., 1995. On the sources and significance of interindustry differences in technological opportunities. *Research Policy* 24, 185–205.

La Banca, C., 2016, The Effects of a Temporary Migration Shock: Evidence from the Arab Spring Migration through Italy, Department of Economics, UCSD UC San Diego, Recent Work Series, eScholarship.

Lewis, E., 2011. Immigration, skill mix, and capital skill complementarity. *The Quarterly Journal of Economics* 126, 1029–1069.

Lindh, T., Malmberg, B., 1999. Age structure effects and growth in the OECD, 1950-1990. *Journal of Population Economics* 12, 431–449.

Maré, D. C., Fabling, R., Stillman, S., 2014. Innovation and the local workforce. *Papers in Regional Science* 93 (1), 183–201.

Moreno, R., Paci, R., Usai, S., 2005. Spatial spillovers and innovation activity in European regions. *Environment and Planning A* 37, 1793–1812.

Moretti, E., 2004. Workers' education, spillovers, and productivity: evidence from plant-level production functions. *American Economic Review* 94, 656–690.

Moser, P., Voena, A., Waldinger, F., 2014. German-Jewish emigrés and U.S. invention. *American Economic Review* 104, 3222–3255.

Moulton, B. R., 1990. An illustration of a pitfall in estimating the effects of aggregate variables on micro units. *The Review of Economics and Statistics* 72, 334–338.

Niebuhr, A., 2010. Migration and innovation: does cultural diversity matter for regional R&D activity? *Papers in Regional Science* 89, 563–585.

Nieto, S., Matano, A., Ramos, R., 2013. Skill mismatches in the EU: immigrants vs. natives. SEARCH Working Paper n. 3.8. Sharing KnowledgE Assets: InteRregionally Cohesive NeigHborhoods (SEARCH) Seventh Framework Programme.

OECD, 2012. *Education at a Glance 2012: OECD Indicators*, Paris: OECD Publishing.

Ottaviano, G., Peri, G., 2006. The economic value of cultural diversity: evidence from US cities. *Journal of Economic Geography* 6, 9–44.

Ottaviano, G. I. P., Peri, G., 2012. Rethinking the effect of immigration on wages. *Journal of the European Economic Association* 10, 152–197.

Ozgen, C., Nijkamp, P., Poot, J., 2012. Immigration and innovation in European regions, in Nijkamp, P., Poot, J., Sahin, M. (Eds.) *Migration impact assessment: New Horizons*, 261-298. Edward Elgar Publishing Limited, Cheltenham (UK) and Northampton (MA).

Ozgen, C., Nijkamp, P., Poot, J., 2013. The impact of cultural diversity on innovation: Evidence from Dutch firm-level data. *IZA Journal of Migration* 2:18.

Parrotta, P., Pozzoli, D., Pytlikova, M., 2014. The nexus between labor diversity and firm's innovation. *Journal of Population Economics* 37, 303–364.

Peri, G., 2012. The effect of immigration on productivity: evidence from U.S. states. *The Review of Economics and Statistics* 94, 348–358.

Peri, G., Requena-Silvente, F., 2010. The trade creation effect of immigrants: evidence from the remarkable case of Spain. *Canadian Journal of Economics* 43, 1433–1459.

Pischke, J.-S., Velling, J., 1997. Employment effects of immigration to Germany: an analysis based on local labor markets. *The Review of Economics and Statistics* 79, 594–604.

Rauch, J. E., Trindade, V., 2002. Ethnic Chinese networks in international trade. *Review of Economics and Statistics* 84, 116–130.

Romer, P., 1990. Endogenous technological change. *Journal of Political Economy* 98, S71–S102.

Sanroma, E., Ramos, R., 2007. Local human capital and productivity: an analysis for the Spanish regions. *Regional Studies* 41, 349–359.

Santos Silva, J. M. C., Tenreyro, S., 2006. The log of gravity. *Review of Economics and Statistics* 88, 641–658.

Simonen, J., McCann, P., 06 2010. Knowledge transfers and innovation: the role of labour markets and R&D co-operation between agents and institutions. *Papers in Regional Science* 89, 295–309.

Stuen, E. T., Mobarak, A. M., Maskus, K. E., 2012. Skilled immigration and innovation: evidence from enrollment fluctuations in the US doctoral programmes. *The Economic Journal* 122, 1143–1176.

Suedekum, J., Wolf, K., Blien, U., 2014. Cultural diversity and local labour markets. *Regional Studies* 48, 173–191.

Venturini, A. and Villosio, C. (2008). Labour-market assimilation of foreign workers in Italy. *Oxford Review* of Economic Policy 24, 517–541.

Wagner, D., Head, K., Ries, J., 2002. Immigration and the trade of provinces. *Scottish Journal of Political Economy* 49, 507–525.

Table 1: OLS estimates of the effect of immigrants on patent applications

	(1)	(2)	(3)	(4)	(5)	(6)
share of immigrants	0.304***	0.082***	0.074***	-0.022*	-0.009	
	(0.018)	(0.015)	(0.015)	(0.013)	0.013	
share of immigrants: HS[a]						-0.001
						(0.054)
share of immigrants: LS						-0.014
						(0.039)
R&D expenditures (% GDP)[b]			0.183	0.353*	0.334*	0.336*
			(0.205)	(0.196)	(0.197)	(0.196)
share value added agriculture			-0.120***	-0.026*	-0.011	-0.011
			(0.012)	(0.013)	(0.013)	(0.013)
share value added services			-0.022***	-0.064	-0.046***	-0.047***
			(0.004)	(0.005)	(0.005)	(0.005)
share value added construction			-0.116***	-0.011	0.014	0.013
			(0.023)	(0.020)	(0.020)	(0.020)
ln(population 2001)				0.302***	0.270***	0.269***
				(0.040)	(0.041)	(0.041)
% active age population (2001)				0.041*	0.043**	0.043**
				(0.022)	(0.021)	(0.021)
% of graduates on pop. 18-64 (2001)				0.184***	0.133***	0.133***
				(0.015)	(0.016)	(0.016)
ln(patent applications percapita in 1995)[c]					0.220***	0.220***
					(0.033)	(0.033)
Year fixed effects	No	Yes	Yes	Yes	Yes	Yes
Region (NUTS-2) fixed effects	No	Yes	Yes	Yes	Yes	Yes
N. observations	824	824	824	824	824	824
R-squared	0.44	0.79	0.82	0.86	0.87	0.87

*** 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-Marfoukof database). [b] only available at the NUTS-2 level. [c] per 1,000 inhabitants
Note. The dependent variable is the logarithm of patent applications per 1,000 inhabitants at the province (NUTS-3) level for Italy, 2003—2010. All independent variables are lagged one year. Standard errors—in parentheses—are clustered at the *Region* × *year* level because of the inclusion of an 'aggregated' variable (Moulton 1990) and robust to heteroskedasticity. HS and LS stand for high skilled and low skilled, respectively.

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

	All immigrants		By skill		
	1st stage (1)	2nd stage (2)	1st stage: HS (3)	1st stage:LS (4)	2nd stage (5)
share of immigrants		-0.046**			
		(0.023)			
share of immigrants: HS[a]					-0.009
					(0.108)
share of immigrants: LS					-0.074
					(0.069)
R&D expenditures (% GDP)[b]	1.014*	0.362*	0.283	0.564*	0.372*
	(0.542)	(0.191)	(0.259)	(0.310)	(0.194)
share value added agriculture	0.112***	-0.004	0.081***	0.033*	-0.006
	(0.032)	(0.012)	(0.015)	(0.017)	(0.014)
share value added services	-0.082***	-0.051***	-0.016***	-0.059***	-0.053***
	(0.014)	(0.006)	(0.006)	(0.009)	(0.006)
share value added construction	-0.036	-0.015	0.012	-0.039	0.013
	(0.051)	(0.020)	(0.023)	(0.031)	(0.020)
ln(population 2001)	0.360***	0.306***	0.183***	0.128**	0.304***
	(0.099)	(0.041)	(0.042)	(0.060)	(0.042)
% active age population (2001)	0.176***	0.041**	0.079***	0.115***	0.041**
	(0.043)	(0.021)	(0.016)	(0.029)	(0.021)
% of graduates on pop. 18-64 (2001)	-0.007	0.142***	0.018	-0.009	0.140***
	(0.027)	(0.016)	(0.014)	(0.015)	(0.017)
ln(patent applications percapita in 1995)[c]	-0.123***	0.212***	-0.024	-0.095***	0.210***
	(0.135)	(0.033)	(0.018)	(0.021)	(0.032)
predicted share of immigrants	0.366***				
	(0.024)				
predicted share of immigrants: HS			0.179***	-0.314***	
			(0.039)	(0.047)	
predicted share of immigrants: LS			0.138***	0.682***	
			(0.032)	(0.040)	
$F-$statistic excluded instruments	225.31		89.34	235.75	
Weak instrument robust inference ($p-$value)[d]		0.05			0.092
N. observations	824	824	824	824	824
R-squared	0.41	0.42	0.41	0.46	0.42

*** 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-Marfoukof database). [b] only available at the NUTS-2 level. [c] per 1,000 inhabitants. [d] Anderson-Rubin Wald test. The test reports the $p-$value on the instrument(s) coefficient(s) in the reduced form estimates.

Note. The dependent variable is the logarithm of patents' applications per 1,000 inhabitants at the province (NUTS-3) level for Italy, 2003-2010. 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. All regressions control for year and 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. HS and LS stand for high skilled and low skilled, respectively.

Table 3: Second stages of firm-level estimates (2SLS)

	All immigrants			By skill		
	Product (1)	Process (2)	Organization (3)	Product (4)	Process (5)	Organization (6)
firm-level variables						
capital intensity	-0.000	0.001***	-0.000	-0.000	0.001***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln(firm size)	0.066***	0.069***	0.059***	0.066***	0.069***	0.059***
	(0.005)	(0.007)	(0.005)	(0.005)	(0.007)	(0.005)
college share	0.003***	0.001*	0.003***	0.003***	0.001*	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R&D intensity	0.018***	0.010***	0.009***	0.018***	0.010***	0.009***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
province-level variables						
share of immigrants	0.009	-0.002	0.000			
	(0.008)	(0.007)	(0.006)			
share of immigrants: HS				0.065	0.043	0.040
				(0.045)	(0.046)	(0.031)
share of immigrants: LS				-0.028	-0.032	-0.026
				(0.023)	(0.026)	(0.018)
ln(population 2001)	-0.030*	-0.004	0.007	-0.034*	-0.006	0.005
	(0.018)	(0.014)	(0.015)	(0.020)	(0.016)	(0.015)
% active age population (2001)	0.005	0.003	-0.014*	0.006	0.004	-0.014*
	(0.009)	(0.007)	(0.008)	(0.009)	(0.007)	(0.008)
% of graduates on pop. 18-64 (2001)	0.006	-0.001	-0.005	-0.002	-0.008	-0.010
	(0.005)	(0.004)	(0.004)	(0.007)	(0.007)	(0.007)
ln(patent applications percapita in 1995)	0.015	-0.002	0.011	0.021*	0.002	0.015*
	(0.012)	(0.009)	(0.008)	(0.013)	(0.012)	(0.009)
$F-$statistic excluded instruments: [a]						
Predicted share of immigrants	41.13	41.13	41.13			
Predicted share of immigrants: HS				26.13	26.13	26.13
Predicted share of immigrants: LS				30.34	30.34	30.34
Weak instrument robust inference (p-value)[b]	0.26	0.80	0.96	0.36	0.36	0.80
N. observations	11214	11214	11214	11214	11214	11214

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

[a] When there is more than one instrument, the Angrist-Pischke multivariate $F-$statistic is reported.

[b] Anderson-Rubin Wald test. The test reports the $p-$value on the instrument(s) coefficient(s) in the reduced form estimates.

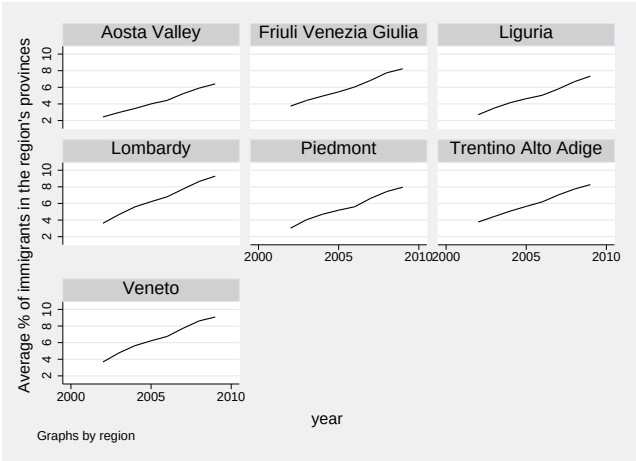
Note. The dependent variables are dichotomous indicators for having introduced product, process and organizational innovations, respectively. All outcomes are modeled using LPMs, and estimated using 2SLS. All regressions control for year, 2-digit industry, and Region fixed effects. Heteroskedasticity-robust standard errors are clustered at the province level since the share of immigrants varies at this level (Moulton 1990). HS and LS stand for high skilled and low skilled, respectively.

Table 4: First stages of firm-level estimates (2SLS)

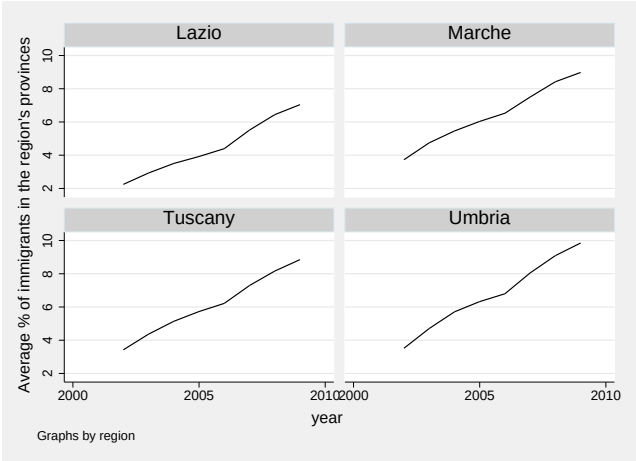
		By skill	
	All immigrants	High-skilled migrants	Low-skilled migrants
	(1)	(2)	(3)
firm-level variables			
capital intensity	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
ln(firm size)	0.017	0.007	0.012
	(0.016)	(0.007)	(0.009)
college share	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
R&D intensity	0.000**	0.000*	0.000**
	(0.000)	(0.000)	(0.000)
province-level variables			
predicted share of immigrants	0.424***		
	(0.066)		
predicted share of immigrants: HS		0.207**	-0.503***
		(0.089)	(0.145)
predicted share of immigrants: LS		0.138	0.922***
		(0.089)	(0.142)
ln(population 2001)	0.417	0.208	0.093
	(0.321)	(0.134)	(0.194)
% active age popoluation (2001)	0.161	0.054	0.146
	(0.187)	(0.070)	(0.128)
% of graduates on pop. 18-64 (2001)	-0.296***	-0.038	-0.181***
	(0.088)	(0.030)	(0.050)
ln(patent applications percapita in 1995)	-0.053	-0.083	-0.010
	(0.189)	(0.072)	(0.112)
N. observations	11214	11214	11214
R-squared	0.41	0.45	0.48

*** significant at 1%; ** significant at 5%; * significant at 10%.
Note. The dependent variables are the total share of immigrants in column (1), the share of low-skilled immigrants in column (2), and the share of high- skilled immigrants in column (3). All regressions control for year, 2-digit industry, and Region fixed effects. Heteroskedasticity-robust standard errors are clustered at the province level. $F-$ statistics for the excluded instruments are reported in the Table 3. HS and LS stand for high skilled and low skilled, respectively.

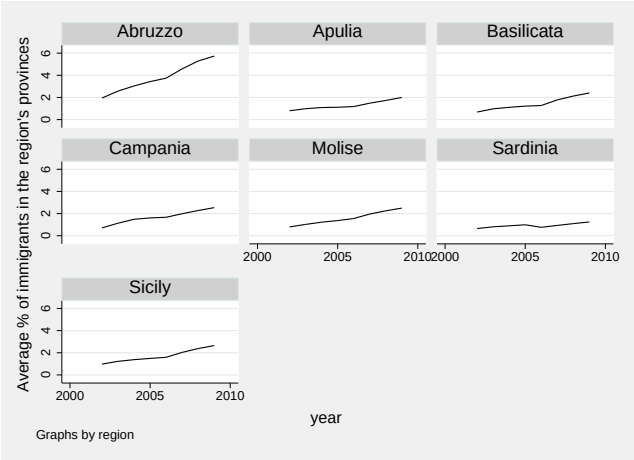
.



(a) Northern Italy



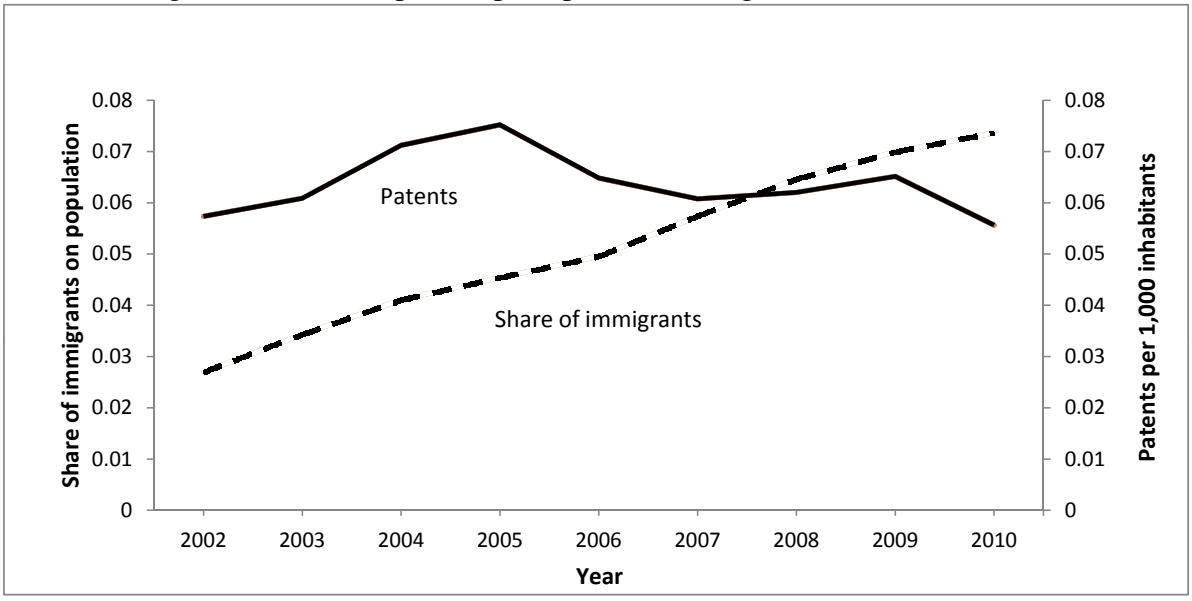
(b) Central Italy



(c) Southern Italy and Islands

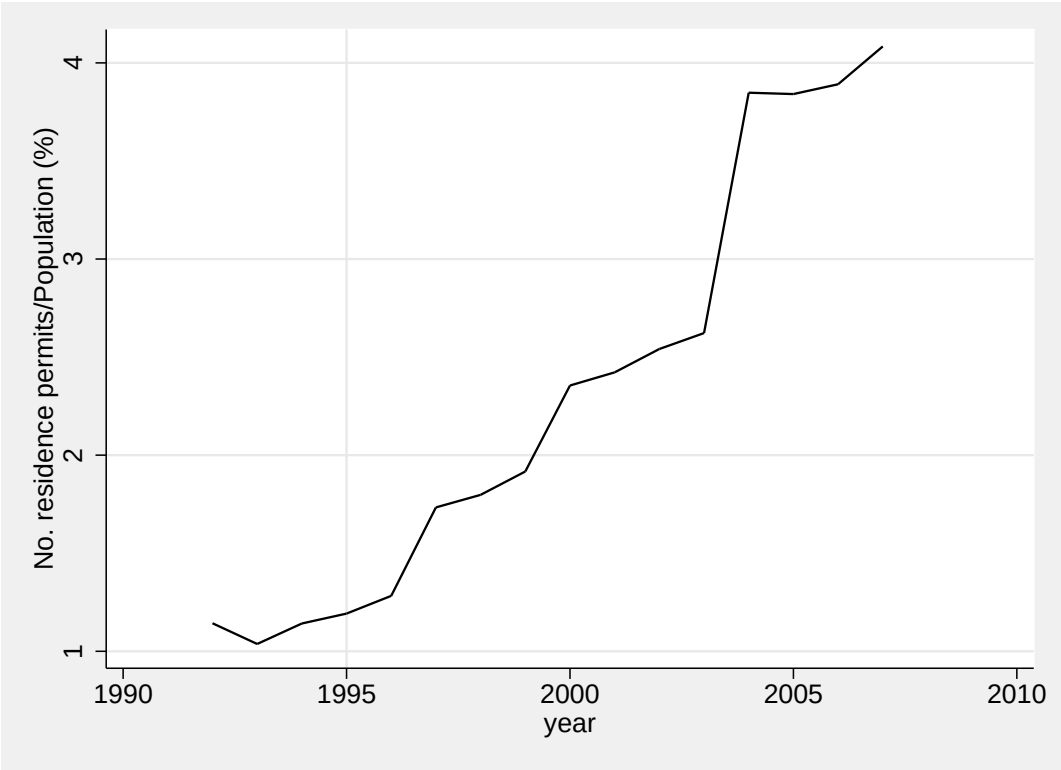
Figure 1: Average provinces' percentage of immigrants on resident population by Region (NUTS-2) 2002-2009 (source: our data)

Figure 2: Trends in patents percapita and immigrants' share 2002-2010



Source: Our data.

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



Note. The series are reported until 2007, as from 2008 onward ISTAT built a times series excluding immigrants from Bulgaria and Romania, who were no longer required residence permits.
Source: ISTAT

Appendices

A Supplementary tables and figures

Table A.1. Sample summary statistics: Province-level analysis

Variables	N. observations	mean	standard deviation
ln(patents per capita)	824	-3.53934	1.333385
R&D expeditures (% GDP)	824	1.048083	0.383977
share of value added in agriculture (%)	824	3.333753	2.230765
share of value added in services (%)	824	69.74159	7.316907
share of value added in construction (%)	824	6.557262	1.303076
ln(population 2001)	824	12.92054	0.705271
% active age population (2001)	824	66.41935	1.595967
% of graduates on pop. 18-64 (2001)	824	10.20474	1.929361
ln(patent applications percapita in 1995)	824	-4.16832	1.40347
share of immigrants (%)	824	4.621399	2.903354
predicted share of immigrants (%)	824	4.13471	2.945269
share of immigrants: HS (%)	824	2.136631	1.336359
share of immigrants: LS (%)	824	2.482353	1.615919
predicted share of immigrants: HS (%)	824	1.924752	1.481597
predicted share of immigrants: LS (%)	824	2.208058	1.505066

Note. Patents percapita are per 1,000 inhabitants. The other variables are described in detail in the main text. Patents data refer to 2003-2010 and the control variables to 2002-2009. The source for patent data is OECD, while the source for all the other data is the Italian National Statistical Institute (ISTAT).

Table A.2. Sample summary statistics: Firm-level analysis

Variables	N. observations	mean	standard deviation
firm-level variables			
product innovations	11214	0.445852	0.497082
process innovations	11214	0.412004	0.492218
organizational innovations	11214	0.264862	0.441279
capital intensity (%)	11214	22.04899	20.46247
ln(firm size)	11214	3.316546	0.84578
firm college share (%)	11214	5.189319	9.674284
R&D intensity (%)	11214	2.141663	5.70512
province-level variables			
ln(population 2001)	11214	13.46809	0.813377
% active age population (2001)	11214	67.19806	1.552555
% of graduates on pop. 18-64 (2001)	11214	10.66688	2.344966
ln(patent applications percapita in 1995)	11214	-3.23511	1.132803
share of immigrants (%)	11214	6.226055	3.001955
predicted share of immigrants (%)	11214	5.17524	3.041754
share of immigrants: HS (%)	11214	2.814585	1.386146
share of immigrants: LS (%)	11214	3.408615	1.689296
predicted share of immigrants: HS (%)	11214	2.365591	1.521301
predicted share of immigrants: LS (%)	11214	2.807386	1.563652

Note. The means of the innovation variables represent the shares of the sample which introduced the various types of innovation. Capital intensity is the nominal capital stock derived from balance sheet data and is evaluated at the net 'historical cost', that is, the cost originally borne by the firm to buy the goods, reduced by the depreciation measured according to the fiscal law, divided by firm's turnover. R&D intensity is the % of R&D expenditures over turnover. The firm's college share is the % of employees with a university degree. The % of active age population is the number of individuals aged 15-64 divided by total population, and multiplied by 100. Patents percapita are per 1,000 inhabitants. The other variables are described in detail in the main text. All statistics are weighted using survey weights. HS and LS stand for high skilled and low skilled, respectively. Data come from two cross-sectional surveys, SIMF (2001-2003, 2004-2006) and EFIGE (2007-2009).

Table A.3. 2SLS estimates with only high-skilled or low-skilled shares of immigrants

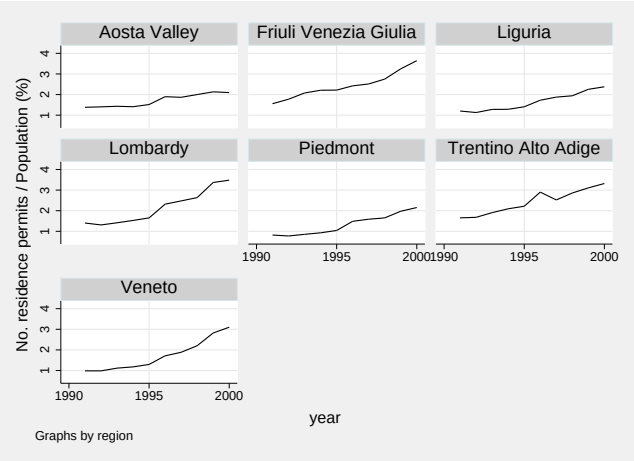
	High-skilled migrants		Low-skilled migrants	
	1st stage (1)	2nd stage (2)	1st stage (3)	2nd stage (4)
share of immigrants: HS[a]		-0.090*		
		(0.054)		
share of immigrants: LS				-0.079**
				(0.036)
R&D expenditures (% GDP)[b]	0.324	0.342*	0.674**	0.374*
	(0.258)	(0.190)	(0.297)	(0.191)
share value added agriculture	0.082***	-0.002	0.028	-0.007
	(0.015)	(0.013)	(0.018)	(0.012)
share value added services	-0.019***	-0.049***	-0.061***	-0.053***
	(0.005)	(0.005)	(0.009)	(0.006)
share value added construction	0.011	0.017	-0.047	0.012
	(0.023)	(0.020)	(0.031)	(0.020)
ln(population 2001)	0.213***	0.301***	0.127**	0.303***
	(0.039)	(0.043)	(0.064)	(0.040)
% active age population (2001)	0.068***	0.042**	0.115***	0.041**
	(0.015)	(0.021)	(0.031)	(0.021)
% of graduates on pop. 18-64 (2001)	0.019	0.142***	-0.030*	0.140***
	(0.013)	(0.017)	(0.015)	(0.015)
ln(patent applications percapita in 1995)[c]	-0.028	0.216***	-0.092***	0.210***
	(0.018)	(0.032)	(0.022)	(0.032)
predicted share of immigrants: HS	0.311***			
	(0.023)			
predicted share of immigrants: LS			0.432***	
			(0.024)	
$F-$statistic excluded instruments	176.72		313.92	
Weak instrument robust inference ($p-$value)[d]		0.10		0.03
N. observations	824	824	824	824
R-squared	0.403		0.437	

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

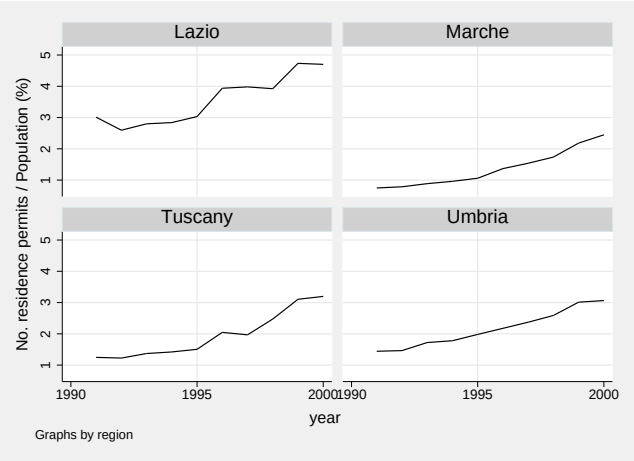
[a] for each province, the total number of immigrants from a given country is split by skill level according to the shares of high-medium skilled and low-skilled emigrants on total emigrants from that country to Italy in 2001 (Docquier-Marfoukof database). [b] only available at the NUTS-2 level. [c] per 1,000 inhabitants. [d] Anderson-Rubin Wald test. The test reports the $p-$value on the instrument(s) coefficient(s) in the reduced form estimates.

Note. The dependent variable is the logarithm of patents' applications per 1,000 inhabitants at the province (NUTS-3) level for Italy, 2003-2010. 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. All regressions control for year and 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. HS and LS stand for high skilled and low skilled, respectively.

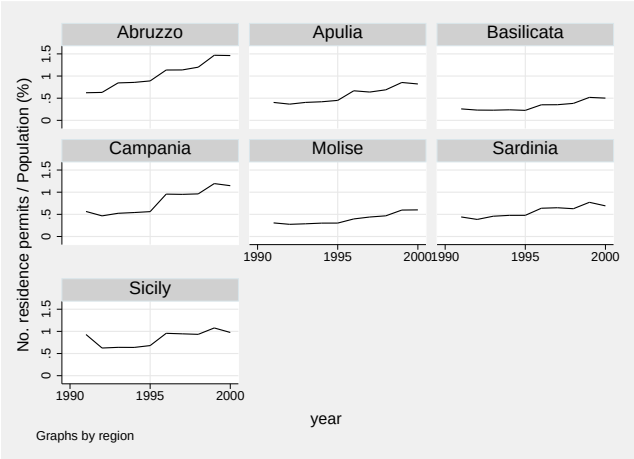
Figure A.1. Residence permits (%) over resident population by Region (NUTS-2) 1992-2000 (source: ISTAT)



(a) Northern Italy



(b) Central Italy



(c) Southern Italy and Islands