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The effect of immigration on innovation in Italy

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ABSTRACT

This paper investigates the effect of immigration on innovation in Italy, a country characterized by prevalently unskilled immigration. After addressing the potential endogeneity of the share of immigrants in the population using immigrant enclaves, no evidence is found of either positive or negative effects of migrants on innovation. This result is robust to allowing for different effects of low- and medium-high-skilled migrants, to using linear and non-linear models, and to considering both province-level data on patent applications and firm-level self-reported measures also capturing innovation adoption.

KEYWORDS

immigration; innovation; patents; provinces; firms; Italy

JEL J2, O3

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INTRODUCTION

Economists have studied extensively the impact of immigration on host countries, natives' wages and employment opportunities, firm productivity, trade creation, and crime, just to mention 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 and another important channel through which immigration can exert an impact on the performance of the host country.

There are several mechanisms through which immigrants could affect innovation. They are well summarized by Ozgen, Nijkamp, and Poot (2013). On the positive side, immigrants may be self-selected (Borjas, 1987) in terms of intelligence, creativity, risk propensity, entrepreneurship and other characteristics that are positively related to innovativeness; immigrants are generally younger than natives, and this may affect their productivity and creativity (Feyrer, 2008; Lindh & Malmberg, 1999); immigrants are more mobile, and workers' mobility is an important source of knowledge spillovers between firms and regions (Faggian & McCann, 2009; Simonen & 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, Glaeser, & Murphy, 1999; Glaeser, 1999) and market size (Acemoglu & Linn, 2004); immigrants are culturally different, and this may increase productivity and innovation in the case that workers with different cultural backgrounds are complementary in production (Ottaviano & Peri, 2006; Parrotta, Pozzoli, & Pytlikova, 2014; Suedekum, Wolf, & Blien, 2014); and 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 (Andersson, Quigley, & Wilhelmsson, 2009; Cowan & Zinovyeva, 2013; Moretti, 2004; Sanroma & Ramos, 2007). These positive effects are more likely to be induced by highly skilled immigrants.

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 & La Ferrara, 2005). These factors may negatively affect many economic outcomes, including innovation. Moreover, while the positive effects of skilled immigrants on the hosting economies are generally undis-

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puted, the impact of low-skilled immigrants has been investigated much less. A large inflow of low-educated immigrants may make a cheap labour force available in traditional sectors, potentially increasing their relative size (Card & Lewis, 2007; De Arcangelis, Di Porto, & Santoni, 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 investment (Lewis, 2011; Peri, 2012).

This brief overview of the potential channels of influence of immigrants on innovation already suggests that, since high- 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 extant research is generally limited to the role played by highly educated immigrants, often individuals with tertiary or post-tertiary education or in research occupations, and is mostly focused on the United States. However, most immigrants are low skilled, even in the United States, and, although skilled immigration is a sizable phenomenon in English-speaking countries – according to Docquier and Marfouk's (2006) data, the percentages of tertiary-educated immigrants in 2001 were 40.3% for Australia, 58.8% for Canada, 34.9% for the UK and 42.7% for the United States – this is much less the case in most European countries for which just the minority of immigrants are skilled (in the following, the terms 'skilled' and 'highly educated' are used interchangeably). Just to give a few figures, according to Docquier and Marfouk (2006), in 2001 the percentages of tertiary-educated immigrants were 16.4% for France, 21.8% for Germany, 15.4% for Italy and 18.5% for 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 this analysis are also likely to be informative for other countries exposed to the recent European refugee crisis. Indeed, political instability and extensive warfare are causing disruption of national educational systems and of the normal economic and social life in large areas of North Africa and the Middle East. These events are feeding important waves of young and low-educated immigrants (LaBanca, 2016), which will increase the share of low-skilled migration in Europe, making it much more similar to Italy's past migration experience.

Secondly, evidence is provided not only for research and development (R&D)-based but also for non-R&D-based innovation.[1] The former, proxied by patent applications, is investigated using a very small geographical scale of analysis – Italian provinces, corresponding to Nomenclature of Territorial Units for Statistics (NUTS)-3 regions – which, compared with larger areas, enables us to control better for differences in institutional and socio-economic factors, which are difficult to observe and which may simultaneously contribute both to attracting new immigrants and to increasing the innovation potential of a region. Since there are several forms of innovation, some of which are non-R&D based and 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 microdata. This is important, because some types of innovations (e.g., process) are less likely to be patented. Moreover, in countries such as Italy, in which the level of formal R&D expenditure is low, an important share of innovations has informal sources. Potential endogeneity issues are tackled using a well-established instrumental variables (IV) strategy based on immigrant enclaves.

The IV estimates demonstrate that the share of immigrants in the province population has no effect on Italian provinces' patent applications. This result is robust to using both linear and non-linear (i.e., quasi-Poisson) models and to considering the separate effects of low- and medium-high-skilled immigrants. Using firm-level data and self-reported measures of firm product, process and organizational innovations does not change the main findings. The lack of effect of increasing waves of low-skilled workers on firms' creation and adoption of innovation in Italy can be explained by their similitude to the natives' skill structure, which prevented a dramatic rise in the relative abundance of low-skilled workers.

The paper is structured as follows. The next section briefly summarizes the recent literature on the effects of immigrants on innovation. The third section describes the Italian context and the main features of Italy's immigration. The data used are described in the Appendices A–C in the supplemental data online. Our empirical strategy and identification are discussed in the fourth section. The results on the effect of immigration on provinces' patent applications and firms' self-reported innovations are commented on in the fifth section. The last section summarizes the main findings and draws some conclusions.

LITERATURE REVIEW

For reasons of space, this review cannot be exhaustive and focuses on some recent contributions that investigate the impact of migrants on innovation, while a comprehensive survey is provided by Jensen (2014).

The bulk of the evidence on the effect of migration on innovation concerns highly skilled migrants. Sizeable positive effects of immigrant college and post-college graduates and immigrant scientists and engineers on patenting per capita are found using both data on states and individual-level data for the United States by Hunt and Gauthier-Loiselle (2010). 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. Evidence exists for the same country that changes in the H-1B visa – allowing US employers to employ foreign workers

temporarily in speciality occupations – influences ethnic patenting in US cities: the total invention increases with more admissions of highly skilled immigrants primarily through the direct contribution of Chinese and Indian inventors (Kerr & Lincoln, 2010). The few papers investigating European countries also keep the main focus on skilled immigration. Diversity in R&D employees turns out to be associated positively with patenting in German regions, but the association loses statistical significance when controlling for regional fixed effects (Niebuhr, 2010). A study for the UK combines Community Innovation Survey data with Labour Force Survey data to build a panel for British local labour market areas (Gagliardi, 2015). This approach enables the author to include in the empirical analysis a large number of control variables compared with other regional-level 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 skilled international migration mostly on process innovation. A cross-country study (Bosetti, Cattaneo, & Verdolini, 2015) focuses on the effect of migrants employed in skilled professions in 20 European countries and reports positive effects both on the number of patent applications and on the number of citations received by published articles.

Other studies do not use geographical-level data but time-series data (Chellaraj, Maskus, & Mattoo, 2008) or data aggregated at the research field (Moser, Voena, & Waldinger, 2014) or university department level (Stuen, Mobarak, & Maskus, 2012), but they always maintain the main focus on skilled migration and demonstrate that migrant scientists and foreign graduate students raise innovation.

Some studies just focus on the total share of migrants without distinguishing them by skill level. Among those, contrasting the UK evidence (Gagliardi, 2015), are the results of a study using firm-level data for New Zealand and reporting no independent effect of local labour force characteristics (the local share of foreign immigrants, highly skilled workers and new arrivals) on a large set of firms' self-reported innovation outcomes (process innovation, product innovation, organizational and management innovations, marketing innovations etc.) after controlling for firm size, industry and expenditure on R&D (Maré, Fabling, & Stillman, 2014).[2] When focusing on worker diversity at the firm level, there is some evidence for Denmark that ethnic diversity facilitates a firm's patenting activity (Parrotta et al., 2014). Firm-level data are also used in a study for Germany that investigates the effect of a firm's share of immigrant workers and employees' ethnic diversity, and finds a negative effect of the former and a positive effect of the latter on product innovation (Ozgen et al., 2013).

Far fewer studies specifically investigate the impact of low-skilled or unskilled migrants on innovation. Lewis (2011) focuses on US metro areas and documents that plants added technology more slowly where immigration (mainly from Mexico) induced the ratio between high-school dropouts and university graduates to grow more quickly and that increases in the relative supply of low-skilled workers were associated with slower growth in the capital–labour and capital–output ratios. Evidence also exists that Mexican immigration promoted the adoption of unskilled-efficient technologies in US states (Peri, 2012). From this scant 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 that explicitly assesses the effect of low-skilled immigration on innovation. Ozgen, Nijkamp, and Poot (2012) use NUTS-2 European regions to estimate the effects of the share of immigrants by continent of origin on innovation, showing some heterogeneity, which, however, can only be related indirectly to the skill levels of immigrants. A very recent study by Jahn and Steinhardt (2016) uses quasi-experimental evidence for Germany by exploiting a placement policy for ethnic German immigrants (*Aussiedler*). Despite the majority of inflows being unskilled, no negative (or even a positive) impact on innovation is found. This is explained by the authors in terms of the positive effects of skilled migrants outweighing those of the low-skilled migrants and of the small cultural and language differences of ethnic Germans – compared with the average migrant – who were legally treated as German citizens from their arrival.

IMMIGRATION IN ITALY

Italy was exposed to a very fast and large wave of immigration during the 2000s, like other European countries. The share of foreigners in the population more than tripled, growing from 2.4% in 2002 to 7.6% in 2010 (Italian National Statistical Institute – ISTAT, Demographic Portal). High growth rates were recorded by both northern and central Italy, while in the south and the islands the share of immigrants remained much lower, rising from 1% to 3%. Unsurprisingly, foreigners tend to settle in the richest regions and in big cities, which offer better employment opportunities: in 2010 the provinces of Milan (north) and Rome (centre) alone accounted for 18% of all Italian immigrants.

Compared with other countries, Italy is mostly characterized by young and low-skilled immigrants (Del Boca & Venturini, 2005). Moreover, Italy is one of the countries with the lowest tendency to attract highly educated immigrants, given its country of origin mix (Organisation for Economic Co-operation and Development (OECD), 2008). 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 (source: ISTAT, Demographic Portal). According to Docquier and Marfouk's (2006) database, for these nationalities in 2001 the shares of highly skilled immigrants (those having completed tertiary education) in the total immigrants to Italy were 10% for Romania and Albania, 6% for Morocco and China, and 35% for Ukraine.

The attractiveness of Italy to low-skilled immigrants, in addition to its favourable location for migration from Africa, can be explained partly by the Italian productive structure, characterized by specialization in traditional industries (De Benedictis, 2005; Larch, 2005) producing and exporting low-skilled, labour-intensive goods. At the same time, Italy performs weakly in science-based industries (telecommunications, measuring and testing instruments, chemical and pharmaceutical products etc.), characterized by intensive use of technical and scientific knowledge inputs. Lack of attractiveness to highly skilled immigrants is also due to the lower returns to human capital for immigrants than for natives. Indeed, human capital acquired in foreign (especially developing) countries is poorly transferable and usually does not enable migrants to gain access to high-paying occupations (Dell'Aringa, Lucifora, & Pagani, 2015).[3]

The skill composition of Italian immigration is reflected in the job qualifications of foreign workers, who are more likely to be employed in low-skilled and low-paid jobs. However, the average level of education of the native population in Italy is not very dissimilar from that of immigrants. Considering the population in the age group 25–64 years, the percentages of migrants (natives) with less than upper-secondary, upper-secondary and tertiary education in 2001 were 52.6% (57.2%), 32.0% (32.0%), and 15.4% (10.8%) respectively (source: Italian Population Census 2001).

The features of the Italian economy are reflected in the country's innovative performance. According to the European Innovation Scoreboard, Italy ranks below the European Union average for the main indicator of innovative capacity.

Finally, note that at first glance the upward trend in the share of immigrants in Italy is not paired with significant changes in the level of innovation, as measured by patent applications: the patenting activity is quite stable over 2002–10, though showing a gap between northern and southern regions.

Summarizing, in Italy immigrants mainly appear to be a source of low-skilled and cheap labour, which is employed in traditional (i.e., low value-added) industries. However, on average, migrants are not less educated than natives, owing to the low educational attainment of the latter. As a consequence, even a sustained inflow of low-skilled migrants is unlikely to have changed substantially the skill structure of the workforce. All these facts must be kept in mind when interpreting the results on the role that immigrants play in Italy's innovation.

EMPIRICAL STRATEGY AND IDENTIFICATION

Province-level data are used to assess the impact of immigration on innovation measured by patent applications. Then a similar analysis is conducted using survey data containing firms' self-reported information on innovation outcomes to account for forms of innovation that are non-R&D based and less formal than patenting. This also allows us to address some of the objections related to the use of patent data. For brevity, the data and variables used in the empirical analysis are described in Appendix A in the supplemental data online.

Province-level analysis

A provincial knowledge production function (KPF), in which the share of immigrants in the population appears among the inputs (e.g., Hunt & Gauthier-Loiselle, 2010), is estimated:

$$\ln PATN_{ijt} = \alpha_0 + \delta_t + \delta_j + \alpha_1 MIGsh_{it-1} + \alpha_2 X_{it-1} + \alpha_3 D_{i2001} + u_{ijt}. \quad (1)$$

where i, j and t are province (NUTS-3), region (NUTS-2) and time subscripts respectively; u_{ijt} is an error term; and α's and δ's the parameters to be estimated. The dependent variable – $\ln PATN_{ijt}$ – is the logarithm of the number of patent applications per 1000 inhabitants. To retain zeros, 0.001 is added to the number of patents before taking the logarithm (a sensitivity analysis to using Poisson pseudo-maximum likelihood estimation is reported in Appendix B in the supplemental data online). All the 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 immigrants' skill levels, this variable is replaced by $MIGHsh_{it-1}$ and $MIGLsh_{it-1}$, which stand for the shares of medium-high- and low-skilled migrants, that is, those with upper-secondary education or more versus those with lower than upper-secondary education (see Appendix A in the supplemental data online) respectively. This classification is preferred to the high- versus medium-low-skilled one, given this study's main focus on low-skilled migrants and the very small share of tertiary-educated migrants in Italy. 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. On the one hand, the main rationale for including controls for the sectoral structure of the local economies 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, Levin, Nelson, & Winter, 1995) – which is in turn correlated with immigrants' employment opportunities and geographical location. On the other hand, on the ground that a large inflow of low-skilled migrants may change the skill structure of a region and its industrial structure, e.g., leading to the expansion of less skill-intensive industries, the industry composition may be a mediating factor, that is, a 'bad control' (Angrist & Pischke, 2009), and should not be included in the regression. However, according to the existing evidence, the effect of immigrants on the sectoral composition of the economy does not appear to be substantial in Italy (De Arcangelis et al., 2015), and especially the IV results, which are based on past immigrants' locations, are not expected to be very sensitive to the inclusion of these controls. For completeness, both specifications including and specifications excluding provinces' sectoral

composition are reported in the paper. D_{i2001} is a vector of covariates that may represent both mediating and confounding factors in the analysis, the values of which have been included in a year predating the estimation period (i.e., 2001 in the analysis spanning 2002–10): the logarithm of population size, the share of active-age population and the college share in the population, as a proxy for human capital. On the one hand, these variables are expected to have a positive effect on innovation; on the other, considering these variables, which are potentially affected by migration, in 2001 ensures they are not affected by migration flows during the estimation period, that is, they are not 'bad controls'. The terms δ_t and δ_j are year and region (NUTS-2) fixed effects respectively. Note that because of the short time interval spanned by the data, province fixed effects are not included in 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. This problem is emphasized, for instance, by Niebuhr (2010), who does not stress the results of the fixed-effects model because of the very small 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 one to use not only time variation but also cross-sectional variation between provinces within the same region. NUTS-2 fixed effects, in turn, enable one to capture all the 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 Bratti, De Benedictis, and Santoni (2014) and Wagner, Head, and Ries (2002) in their analyses of the effect of immigration on trade.[4]

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 firm innovation. The main difference is that here the dependent variables are dichotomous indicators for firms' self-reports of having introduced product, process and organizational innovations in the last three years:

$$INN_{kit,\,t+3} = \alpha_0 + \delta_t + \delta_j + \delta_s + \alpha_1 MIGsh_{it} + \alpha_2 X_{kt} + \alpha_3 D_{i2001} + u_{kit,\,t+3} \qquad (2)$$

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 $u_{kit,\,t+3}$ is an error term. δ_t and δ_j are time and region fixed effects respectively; while δ_s stands for two-digit industry fixed effects. Variables that are found to affect innovation at the firm level by previous studies (Gagliardi, 2015; Maré et al., 2014) are included among the firm-level covariates 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. D_{i2001} is the vector of province time-invariant covariates described above.

Identification

Ordinary least squares (OLS) gives consistent estimates only if, conditional on the observables included in the innovation equation, the error terms of equations (1) and (2) are uncorrelated with the share of immigrants. There are several reasons why this assumption may fail. Shocks to the local demand, e.g., increased foreign demand for a locally manufactured product, could attract more immigrants and have positive effects on innovation. The identification of the effect of immigrants, therefore, requires 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 IV estimator. This variation need not be completely random but must be uncorrelated with the unobserved innovation capacity of a province (or a firm) conditional on the regressors. To build an instrument for the share of immigrants, the procedure proposed by Altonji and Card (1991) is followed. This strategy is already extensively used in the empirical literature on immigration (for some recent applications, see Gagliardi, 2015; Hunt & Gauthier-Loiselle, 2010; Lewis, 2011; and Peri, 2012). The identification is based on immigrant enclaves. The idea is that new 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 $MIGsh$ 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 the sample. In more detail, the instrument is built as follows. The yearly stock of immigrants in Italy from country g as a whole (M_{gt}) is imputed to provinces according to the distribution of nationalities across provinces in 1995 (θ_{gi1995}). Formally:

$$\hat{M}_{git} = \theta_{gi1995} M_{gt}. \qquad (3)$$

All immigrants' predicted stocks by nationality ($\hat{M}_{git}$) are aggregated at the province level to compute the predicted total stock of immigrants in province i at time t and then divided by the predicted total province population, in this way obtaining the instrument, that is, the predicted immigrants' share:

$$\widehat{MIGsh}_{it} = \sum_{g=1}^{Gi1995} \hat{M}_{git} / \widehat{POP}_{it}, \qquad (4)$$

where $Gi1995$ is the number of ethnic groups present in province i in 1995). In the same way as for immigrants, the predicted total population $\widehat{POP}_{it}$ is computed by apportioning the national population in each year to provinces according to the 1995 province distribution. This avoids the denominator of the ratio being endogenous, as it includes the stock of migrants.

The instrument contains two components. The first is the total stock of individuals by nationality in Italy,

which should be uncorrelated with each single province's supply-and-demand shocks exerting an impact 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 seven years later, conditional on the observables included in the regressions. The main identifying assumption is that, conditional on the covariates, the between-province variation within the same NUTS-2 region in the distribution of immigrants by different nationalities in 1995 was approximately random with respect to provinces' future innovation prospects. Some factors that 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 are controlled for in equation (1). Until 1995, the percentage of immigrants in the population was quite constant and 1995 predates the period of rapid inflow of immigrants into Italy. The small size of the ethnic network in 1995, together with the skill composition of migrants, makes it very unlikely that immigrants in Italy had a deep knowledge of the innovation capacity of the provinces where they were located and that this was an important determinant of their location choice (unlike, for instance, the skilled immigrants to the Silicon Valley in the United States). This does not completely exclude the possibility, however, that some immigrants might have partly decided their location in 1995 on the basis of unobserved variables that are correlated with current innovation, since the innovation process is quite persistent over time. Thus, to strengthen the credibility of the exogeneity assumption, the logarithm of provinces' per capita patent applications in 1995 is included in the regressions. After the inclusion of this additional control, the only variation in immigrants' past locations that is used for identification is uncorrelated with provinces' past innovation. Past patent applications are also included in the regressions estimated with OLS for the sake of comparability.

A similar procedure is followed to build the excluded instrument for medium-high- and low-skilled immigrants (described in greater detail in Appendix A in the supplemental data online).

RESULTS

Province-level results

This section presents the results from the estimation of the impact of immigration on provinces' innovation as described in equation (1). The OLS estimates are shown in columns (1)–(3) of Table 1. Column (1) presents the specification only including year and region fixed effects. A very significant positive correlation between the share of immigrants and the patent applications emerges. An increase in the share of immigrants by 1 percentage point is associated with a 7.2% increase in patent applications (per 1000 inhabitants). In column (2) control variables for R&D employment, population size, the percentage of the active-age population, the percentage of university graduates and patent applications in 1995 are included in the innovation equation. The coefficient on the share of immigrants reduces sharply (0.025), but is still positive and statistically significant at the 5% level. The elasticity of patent applications with respect to the provincial population is 0.251. A 1 percentage point increase in the shares of the active-age population and of university graduates is associated with 5.5% and 3.9% increases in patent applications respectively. The elasticity of current patent applications with respect to patent applications in 1995 is 0.316, showing the persistence of innovation over time. Surprisingly, the coefficient on the percentage of employees in R&D-related activities is not statistically significant. One reason is the prevalence of non-R&D-based innovation in Italy.[5] Column (3) includes controls for the employment shares in 15 industries. The coefficient on the share of migrants is further reduced in magnitude and becomes very close to zero. Thus, provinces' industrial structure is mainly responsible for the positive association observed in column (2). Columns (4) and (5) of Table 1 report the two-stage least squares (2SLS) estimates, which aim to address the potential endogeneity of the share of migrants. The corresponding first-stage results are shown in columns (1) and (2) of Table 2, the first controlling and the second not controlling for provinces' industrial structure. In both columns the coefficient on the predicted share of migrants is significant at the 1% level, with F-statistics of 307.49 and 220.04 respectively. In spite of the strength of the instrument, the second-stage coefficient on the share of migrants is not statistically different from zero in columns (4) and (5) of Table 1.

Table 3 reports the results of the specifications including the share of medium-high- and low-skilled migrants. The OLS estimates are shown in columns (1)–(3) and the 2SLS estimates in columns (4) and (5). In column (1), which only controls for year and region fixed effects, both medium-high- and low-skilled immigrants are positively associated with patent applications. A 1 percentage point increase in the share of medium-high-skilled migrants in the population is associated with a 12.6% increase in patenting per capita. The magnitude of the coefficient is very close to that estimated by Hunt and Gauthier-Loiselle (2010), who reported an increase of 12–15% in patenting as the result of raising the immigrant college share in the population by 1 percentage point. Adding control variables for R&D effort, other potential confounding factors and lagged innovation in column (2) reduces the magnitude of the coefficient on the share of medium-high-skilled migrants (0.017), but increases that for low-skilled immigrants (0.061), which is significant at the 1% level. This positive association is also robust to the inclusion of provinces' industrial structure in column (3), which only causes a small reduction in the coefficient (0.043). However, the results change dramatically using 2SLS. Columns (3) and (4) of Table 2 report the first-stage results of the specification excluding and columns (5) and (6) the results of that including industries' employment shares respectively. In all cases, the predicted shares of immigrants are very good predictors of the actual shares of immigrants. The F-statistics are never below 20. The

Table 1. Ordinary least squares (OLS) and two-stage least squares (2SLS) estimates of the effect of immigrants on patent applications.

	OLS estimates			2SLS estimates	
	(1)	(2)	(3)	(4)	(5)
share of immigrants (%)	0.072***	0.025**	0.004	0.020	–0.018
	(0.016)	(0.013)	(0.013)	(0.021)	(0.024)
% employed in R&D activity		–0.006	–0.004	–0.006	–0.002
		(0.011)	(0.012)	(0.011)	(0.012)
ln(population 2001)		0.251***	0.178***	0.256***	0.193***
		(0.043)	(0.044)	(0.044)	(0.045)
% active age population (2001)		0.055***	0.057***	0.054***	0.057***
		(0.021)	(0.022)	(0.021)	(0.021)
% of university graduates on pop. 18–64 (2001)		0.039***	0.108***	0.039***	0.109***
		(0.014)	(0.017)	(0.014)	(0.017)
ln(patent applications per capita in 1995)[a]		0.316***	0.226***	0.316***	0.221***
		(0.030)	(0.033)	(0.029)	(0.033)
Share of employment (%)[b] *(science-based manufacturing)*					
agriculture, forestry and fishing			–0.027**		–0.026**
			(0.011)		(0.011)
mining and quarrying			–0.208***		–0.218***
			(0.052)		(0.052)
supplier-dominated manufacturing			–0.010		–0.010
			(0.010)		(0.010)
scale-intensive manufacturing			0.017		0.015
			(0.010)		(0.010)
specialized-suppliers manufacturing			0.007		0.008
			(0.011)		(0.011)
construction			–0.014		–0.015
			(0.013)		(0.012)
trade and accommodation			–0.011		–0.014
			(0.011)		(0.011)
transportation and communication			–0.049***		–0.052***
			(0.017)		(0.017)
financial and real-estate activities			0.005		0.005
			(0.020)		(0.019)
professional and technical activities			–0.030**		–0.032**
			(0.015)		(0.014)
public administration			–0.042***		–0.043***
			(0.013)		(0.012)
education and human health			–0.011		–0.014
			(0.012)		(0.012)
social work activities			–0.041***		–0.043***
			(0.016)		(0.015)
other services			–0.026		–0.030
			(0.027)		(0.027)

(*Continued*)

Table 1. Continued.

	OLS estimates			2SLS estimates	
	(1)	(2)	(3)	(4)	(5)
Weak instrument robust inference (*p*-value)[c]				0.37	0.44
Observations	927	927	927	927	927
R^2	0.78	0.86	0.87	0.36	0.43

Notes. The dependent variable is the logarithm of patents' applications per 1000 inhabitants at the province (NUTS-3) level for Italy, 2002–10. All models include year and region (NUTS-2) fixed effects. Standard errors are robust to heteroskedasticity.
[a]Per 1000 inhabitants.
[b]The 15 sectors of economic activity are built by aggregating ATECO two-digit codes (the classification is available from the authors upon request). The omitted category (science-based manufacturing) is considered as the most innovative sector.
[c]The test reports the *p*-value on the coefficient(s) of the instrument(s) in the reduced form estimates.
***Significant at 1%; **significant at 5%; *significant at 10%.

Table 2. First stages of province-level estimates.

	All immigrants		By skill			
			High skilled	Low skilled	High skilled	Low skilled
	(1)	(2)	(3)	(4)	(5)	(6)
predicted share of immigrants (%)	0.453***	0.403***				
	(0.026)	(0.027)				
predicted share of immigrants: HS (%)[a]			0.233***	0.072	0.191**	–0.001
			(0.073)	(0.110)	(0.076)	(0.112)
predicted share of immigrants: LS (%)[a]			0.063	0.383***	0.054	0.392***
			(0.061)	(0.099)	(0.065)	(0.103)
% employed in R&D activity	0.013	0.048*	0.007	–0.026	0.030	–0.009
	(0.024)	(0.028)	(0.018)	(0.028)	(0.021)	(0.030)
ln(population 2001)	0.172*	0.172*	–0.003	0.176***	–0.006	0.145**
	(0.094)	(0.096)	(0.067)	(0.068)	(0.071)	(0.073)
% active age population (2001)	0.157***	0.181***	0.055*	–0.014	0.081**	–0.027
	(0.055)	(0.053)	(0.032)	(0.039)	(0.032)	(0.041)
% of university graduates on pop. 18–64 (2001)	–0.225***	–0.098***	0.033	–0.198***	0.059**	–0.149***
	(0.031)	(0.033)	(0.024)	(0.031)	(0.027)	(0.044)
ln(patent applications per capita in 1995)[b]	0.020	–0.107**	0.011	0.052	–0.041	–0.039
	(0.053)	(0.047)	(0.036)	(0.049)	(0.037)	0.051
Share of employment (%)[c] (science-based manufacturing)						
agriculture, forestry and fishing		–0.001			–0.019	–0.026
		(0.017)			(0.013)	(0.017)
mining and quarrying		–0.250**			–0.058	–0.108
		(0.105)			(0.077)	(0.092)
supplier-dominated manufacturing		0.008			–0.026**	–0.008
		(0.020)			(0.012)	(0.016)
scale-intensive manufacturing		–0.051***			–0.051***	–0.038**
		(0.019)			(0.014)	(0.016)
specialized-suppliers manufacturing		–0.008			–0.023	–0.006
		(0.022)			(0.014)	(0.020)
construction		–0.053**			–0.060***	–0.041

(*Continued*)

Table 2. Continued.

	All immigrants		By skill			
			High skilled	Low skilled	High skilled	Low skilled
	(1)	(2)	(3)	(4)	(5)	(6)
		(0.024)			(0.018)	(0.027)
trade and accommodation		–0.072***			–0.063***	–0.054***
		(0.019)			(0.014)	(0.016)
transportation and communication		–0.067**			–0.032	–0.054**
		(0.033)			(0.022)	(0.027)
financial and real-estate activities		–0.057			0.014	0.001
		(0.044)			(0.044)	(0.063)
professional and technical activities		–0.053*			–0.077***	–0.046
		(0.030)			(0.024)	(0.033)
public administration		–0.018			–0.047***	–0.055**
		(0.021)			(0.014)	(0.026)
education and human health		–0.100***			–0.067***	–0.068***
		(0.020)			(0.015)	(0.020)
social work activities		–0.073**			–0.017	0.026
		(0.030)			(0.027)	(0.031)
other services		–0.216***			–0.095**	–0.091
		(0.065)			(0.048)	(0.080)
F-statistic-excluded instruments	307.49	220.04	40.13	57.98	23.18	39.26
Observations	927	927	927	927	927	927

Notes: The dependent variables are the total share of immigrants in columns (1) and (2), the share of high-skilled immigrants in columns (3) and (5), and the share of low-skilled immigrants in columns (4) and (6). All models include year and region (NUTS-2) fixed effects. Standard errors are robust to heteroskedasticity.
[a]HS and LS= high- and low-skilled respectively. The former are defined as those with at least secondary education.
[b]Per 1000 inhabitants.
[c]The 15 sectors of economic activity are built by aggregating ATECO two-digit codes (the classification is available from the authors upon request). The omitted category (science-based manufacturing) is considered as the most innovative sector.
***Significant at 1%; **significant at 5%; *significant at 10%.

difference in the magnitude of the *F*-statistics for medium-high- and low-skilled immigrants can be explained in the light of the findings of Beine and Salomone (2013), which show that networks favour 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 second-stage results in columns (4) and (5) of Table 3 demonstrate that neither medium-high- nor low-skilled migrants have an effect on patent applications after potential endogeneity is addressed. The Anderson–Rubin Wald test indicates that this conclusion is robust to potential weak-instrument problems, which, however, are not detected in the first stage. These results are robust to using a Poisson pseudo-maximum likelihood (PPML) model reported in Appendix B in the supplemental data online.

This lack of evidence of an effect of medium-high-skilled migrants on patenting in Italy, though contrasting the US-based results, is not surprising. Since the focus of the paper is on low-skilled migrants (i.e., those without a high-school diploma) and no information on foreign workers holding a doctorate or on their field of specialization is available at the province level for the years covered by this study, the share of medium–high-skilled migrants is built as a residual category including all migrants with upper-secondary education or more. However, the evidence from the United States shows that the bulk of the positive effect of skilled migration on patenting is due to a combination of self-selection and composition effects, being ascribable to foreign doctorate students, who tend to specialize in science and technology – in which patenting occurs more frequently – more than native students, and to immigrant scientists and engineers.

At first glance, somehow more surprising is the fact that the abundance of unskilled labour does not appear to have changed the incentives to innovate in a country such as Italy, which has historically been characterized by industrial specialization based on mature and low-value-added industries, in which those workers are most likely to be employed. However, this could partly be explained by the low educational attainment of the native population: unlike the United States, in Italy the inflow of low-educated workers from abroad did not substantially change the

Table 3. Ordinary least squares (OLS) and two-stage least squares (2SLS) estimates of the effect of high- (HS) and low-skilled (LS) immigrants on patent applications.

	OLS estimates			2SLS estimates	
	(1)	(2)	(3)	(4)	(5)
share of immigrants: HS (%)[a]	0.126***	0.017	0.012	–0.065	–0.034
	(0.031)	(0.022)	(0.022)	(0.271)	(0.260)
share of immigrants: LS (%)[a]	0.045**	0.061***	0.043***	0.077	–0.017
	(0.021)	(0.017)	(0.016)	(0.156)	(0.140)
% employed in R&D activity		–0.004	–0.004	–0.003	–0.002
		(0.011)	(0.012)	(0.013)	(0.015)
ln(population 2001)		0.237***	0.159***	0.243***	0.192***
		(0.042)	(0.043)	(0.054)	(0.051)
% active age population (2001)		0.062***	0.063***	0.062**	0.056*
		(0.021)	(0.022)	(0.027)	(0.032)
% of university graduates on pop. 18–64 (2001)		0.044***	0.110***	0.053	0.110***
		(0.014)	(0.017)	(0.045)	(0.041)
ln(patent applications per capita in 1995)[b]		0.313***	0.231***	0.312***	0.221***
		(0.029)	(0.033)	(0.030)	(0.033)
Share of employment (%)[c] (science-based manufacturing)					
agriculture, forestry and fishing			–0.026**		–0.027**
			(0.011)		(0.011)
mining and quarrying			–0.199***		–0.217***
			(0.051)		(0.052)
supplier-dominated manufacturing			–0.009		–0.011
			(0.010)		(0.011)
scale-intensive manufacturing			0.019*		0.014
			(0.011)		(0.013)
specialized-suppliers manufacturing			0.007		0.007
			(0.011)		(0.012)
construction			–0.012		–0.017
			(0.013)		(0.017)
trade and accommodation			–0.007		–0.016
			(0.011)		(0.015)
transportation and communication			–0.046***		–0.053***
			(0.017)		(0.017)
financial and real-estate activities			0.004		0.006
			(0.020)		(0.020)
professional and technical activities			–0.027*		–0.034*
			(0.015)		(0.019)
public administration			–0.039***		–0.045***
			(0.013)		(0.014)
education and human health			–0.008		–0.016
			(0.012)		(0.014)
social work activities			–0.042***		–0.041**
			(0.015)		(0.016)
other services			–0.022		–0.031
			(0.027)		(0.030)

(*Continued*)

Table 3. Continued.

	OLS estimates			2SLS estimates	
	(1)	(2)	(3)	(4)	(5)
Weak instrument robust inference (*p*-value)[d]				0.56	0.73
Observations	927	927	927	927	927
R^2	0.79	0.86	0.88	0.36	0.42

Notes: The dependent variable is the logarithm of patents' applications per 1000 inhabitants at the province (NUTS-3) level for Italy, 2002–10. All models include year and region (NUTS-2) fixed effects. Standard errors are robust to heteroskedasticity.
[a]HS and LS = high- and low-skilled respectively. The former immigrants are defined as those with at least secondary education.
[b]Per 1000 inhabitants.
[c]The 15 sectors of economic activity are built by aggregating ATECO two-digit codes (the classification is available from the authors upon request). The omitted category (science-based manufacturing) is considered as the most innovative sector.
[d]The test reports the *p*-value on the coefficient(s) of the instrument(s) in the reduced form estimates.
***Significant at 1%; **significant at 5%; *significant at 10%.

Table 4. Two-stage least squares (2SLS) estimates of the effect of immigrants on firms' self-reported innovation.

	Second stage			First stage
	Product	Process	Organization	
	(1)	(2)	(3)	(4)
firm-level variables capital intensity	–0.000	0.001***	–0.000	–0.000
	(0.000)	(0.000)	(0.000)	(0.000)
ln(firm size)	0.066***	0.069***	0.059***	0.017
	(0.005)	(0.007)	(0.005)	(0.016)
college share	0.003***	0.001*	0.003***	–0.000
	(0.001)	(0.001)	(0.001)	(0.000)
R&D intensity	0.018***	0.010***	0.009***	0.000**
	(0.002)	(0.001)	(0.001)	(0.000)
province-level variables share of immigrants (%)	0.009	–0.002	0.000	
	(0.008)	(0.007)	(0.006)	
predicted share of immigrants (%)				0.424***
				(0.066)
ln(population 2001)	–0.030*	–0.004	0.007	0.417
	(0.018)	(0.014)	(0.015)	(0.321)
% active age population (2001)	0.005	0.003	–0.014*	0.161
	(0.009)	(0.007)	(0.008)	(0.187)
% of university graduates on pop. 18–64 (2001)	0.006	–0.001	–0.005	–0.296***
	(0.005)	(0.004)	(0.004)	(0.088)
ln(patent applications per capita in 1995)	0.015	–0.002	0.011	–0.053
	(0.012)	(0.009)	(0.008)	(0.189)
F-*statistic-excluded instruments*				
Predicted share of immigrants	41.13	41.13	41.13	
Weak instrument robust inference (*p*-value)[a]	0.26	0.80	0.96	
Observations	11,214	11,214	11,214	11,214

Notes: The dependent variables in columns (1)–(3) are dichotomous indicators for having introduced product, process and organizational innovations respectively. The dependent variable in column (4) is the total share of immigrants. All outcomes are modelled using linear probability models (LPMs), and estimated using 2SLS. All regressions control for year, two-digit industry, and (NUTS-2) region fixed effects. Heteroskedasticity-robust standard errors are clustered at the province level.
[a]Anderson–Rubin Wald test. The test reports the *p*-value on the coefficient(s) of the instrument(s) in the reduced form estimates.
***Significant at 1%; **significant at 5%; *significant at 10%.

educational structure of the labour supply available to firms. A cautionary note is, however, in order. This lack of evidence may also be due to a 'wrong' choice of the outcome variable. For instance, immigrants may affect the introduction or adoption of process innovations, and patents may not be able to capture such phenomena. Indeed, on the one hand, process innovations are less frequently patented, and, on the other, the adoption of (already-existing) innovations is not measured by patent applications. This motivates the use of firm-level survey data in the next section. Survey data enable the use of self-reported measures of product, process and organization innovations, addressing some of the potential weaknesses of the analysis using patent data.

Firm-level results on the effect of the local share of migrants

Due to the high number of outcomes considered (product, process and organizational innovations), only the linear probability model (LPM) 2SLS results are presented here. The rules of the ADELE laboratory (see Appendix A in the supplemental data online), which provided the province-level skill structure of migrants, do not allow researchers to merge external microdata with data deposited at ADELE. This prevented us from using the province shares of medium-high- and low-skilled migrants in this section. Information on the skill structure of migrants hired by firms is not available in the survey data, and this variable cannot be included in the estimation of equation (2). Thus, in this section the main focus remains on the effect of the local share of migrants on firms' self-reported innovation. However, based on the credible assumptions that the local availability of migrants positively affects a firm's likelihood of hiring foreign workers and that the effects of the local and the firm shares of migrants on innovation do not have opposite signs, the estimated effect is also informative regarding the role of the firm's share of migrants, partly capturing the effect of this omitted variable.

Standard errors are clustered at the province level, that is, the level of variation of the instrument (Moulton, 1990). The first-stage results are presented in column (4) of Table 4. The first-stage coefficient of the share of immigrants (0.424) is very similar to that estimated in the province-level analysis, and the F-statistic is about 41. The coefficient on the share of migrants in the second stage in columns (1)–(3) of Table 4 is always very close to zero and never statistically significant at conventional levels. The results are therefore consistent with those reported for New Zealand by Maré et al. (2014), who also use firm self-reported measures of innovation and do not control for a firm's share of migrants.

All in all, the results in this section suggest that the conclusions of the previous section are not driven by the use of patent data and are robust to using other proxies for innovation that are more suitable for capturing both the adoption and the introduction of non-R&D-based innovations by firms. It must be kept in mind that the coefficient on the local share of migrants estimated in Table 4 partly captures the effect of the share of migrants working inside the firm, which is omitted from the regression because of data unavailability. Very much like the province-level regressions, which estimated the overall effect of migrants on a province's innovation, accounting for both the internal (i.e., the share of migrants in firm employees) and the external (or spillover) effects of the local share of migrants, the estimates in this section also pool the two effects together.[6]

Table C10 in Appendix C in the supplemental data online reports the estimates of probit and IV-probit models, which explicitly account for the dichotomous nature of the self-reported innovation outcomes. The results confirm those obtained using the LPM.

CONCLUSIONS

This paper investigates the effect of the local share of immigrants in the population on both Italian provinces' patent applications and firms' self-reported innovation, which, unlike the former, encompasses both R&D- and non-R&D-based innovation and is a proxy for the adoption as well as the production of new knowledge.

Unlike most work in this literature, this study is not centred on the effects of skilled immigration but focuses on the general impact of immigration and makes an attempt to identify the effect on innovation of, especially, low-educated immigrants. This also motivates the focus on Italy, where most immigrants are low skilled.

After addressing the potential endogeneity of the share of immigrants in the province population using immigrant enclaves, no evidence is found of either positive or negative effects of migrants on innovation. This result is robust to allowing for different effects of low- and medium-high-skilled migrants, to using linear and non-linear (i.e., quasi-Poisson) models, and to considering both province-level data on patent applications and firm-level self-reported measures of innovation.

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DISCLOSURE STATEMENT

No potential conflict of interest was reported by the author(s).

SUPPLEMENTAL DATA

Supplemental data for this article can be accessed at https://doi.org.10.1080/00343404.2017.1360483

NOTES

1. Non-R&D-based innovations include all innovations based on informal activities (e.g., learning by doing/using), the adoption of innovation through the market (e.g., suppliers' innovation) or the imitation of new products.
2. These results are at odds with the local labour market areas' 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 them by skill level.
3. However, this is not a peculiar feature of the Italian economy. Nieto, Matano, and Ramos (2015), for instance, find similar evidence for other European countries.
4. Fixed effects defined at the same level as the unit of analysis are more often included by authors using census data and a very long time span (e.g., Hunt & Gauthier-Loiselle, 2010).
5. Interestingly, unlike in the linear model, the R&D employment share is positively associated with patent applications in the PPML model omitting industry fixed effects, and ceases to be statistically significant after their inclusion (see Appendix B in the supplemental data online). This points to two facts. First, patenting is concentrated in few sectors, which also invest more in R&D. Second, the PPML estimator may be able to capture better than the linear model some features of patent data. Indeed, the PPML estimator is optimal when the conditional variance is proportional to the conditional mean, which allows for both under- and over-dispersion in the data, but delivers consistent estimates even if this assumption is violated (Santos Silva & Tenreyro, 2006).
6. On the contrary, if one were able also to include the share of migrants in firm employment in equation (2), the coefficient on the local share of migrants would only estimate the spillover effect on innovation.

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