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# The heterogenous relationship between migration and innovation: evidence from Italy

This paper offers a novel take on the relationship between migration and regional innovation by analyzing the impact of both international and internal migration flows across Italian provinces, by skill level, and on three types of intellectual property rights (IPRs), namely patents, trademarks and design rights. Allowing us to capture innovation beyond technology and high-tech manufacturing, our results shed light on the relationship between different types of migrant human capital and this array of innovative outcomes. Focusing on Italian provinces in the period 2003–2012, our empirical analysis reveals that internal migration is more significantly related to innovation than international migration. Moreover, medium- and high-skilled migrants are positively associated with all three types of IPRs, while low-skilled migration has a negative association. There are also significant differences across provinces, with a clear distinction between the more economically developed Northern provinces and the rest of Italy.

Keywords: International migration; internal migration; innovation; intellectual property rights

JEL classification codes: O15; R23; O34, F22



## 1. Introduction

Economists and geographers have long stressed the need for a deeper understanding of the economic consequences of migration on growth and, more recently, on resilience (Boubtane, Dumont, and Rault 2016; Cushing and Poot 2004; Faggian, Rajbhandari, and Dotzel 2017; Hunt and Gauthier-Loiselle 2010). Although research on this relationship is abundant, the role of migration on local innovation is investigated less (Zhao and Li 2021). Given that innovation is a key driver of economic growth and regional resilience, an emerging research strand focuses on whether specific groups of migrants might play distinct roles depending on their skills (Granato et al. 2015; Nathan 2014).

Migration has the potential to change the demographic composition and skills of the workforce. Empirical analyses have shown how an increase in human capital stocks, resulting from migration, stimulates knowledge creation processes and increases the level of creativity and productivity of local networks (Alesina and La Ferrara 2005; Amendola, Barra, and Zotti 2020; Gagliardi 2015). However, other authors have found a negative or neutral effect of migration on innovation (Venturini, Montobbio, and Fassio 2012; Bratti and Conti, 2018). For example, an inflow of low-skilled labor can result in the availability of a cheap workforce in traditional sectors, thereby increasing their relative size (De Arcangelis, Di Porto, and Santoni 2015) and discouraging investment in capital-intensive technologies, with negative effects on innovation (Lewis 2011; Peri 2012).

As a result, whether or not migration has positive effects on innovation needs to be empirically established. Moreover, research has mostly focused on international migration, largely because of its greater visibility in policy debates. However, most migration flows are actually internal and have resulted in regional differences in economic growth and productivity levels (Fratesi and Percoco 2014; Basile et al. 2019).

The objective of this paper is to provide nuanced evidence on the impact of migration on innovation in Italian provinces over a ten-year period (2003–2012), by simultaneously looking at both internal and international migrants and different types of innovation outcomes. Italy is an interesting case study because the country has experienced a recent wave of international migration of mostly less educated workers from developing countries (Bratti and Conti 2018). At the same time, there has been an increasingly selective internal migration of the most qualified individuals from the less developed Southern provinces to the richer ones, with clear effects on the long-standing issue of regional divergence.

To assess the impact of skill-specific international and internal migration flows on regional innovation, we employ a knowledge production function (KPF) approach, where the three IPRs metrics represent different innovation outputs. To the best of our knowledge, this is the first migration study to exploit a broader set of innovation metrics. Specifically, we combine patents with trademark and design applications, following recent efforts to expand regional innovation metrics beyond patents only (Capello and Lenzi 2018, Castaldi and Mendonça, 2022).

The results of our empirical analysis for the period 2002–2013 indicate that internal migration in Italy was more significant for local innovation than international migration. This bears important implications, and is a warning against solely using international migration as an explanatory variable for innovation while disregarding internal migration flows. Another key result is that medium- to high-skilled internal migration is positively associated with all three types of regional innovation while low-skilled migration has a negative association. Moreover, differences emerge across macro-areas, with a clear distinction between the more economically developed Northern provinces and the rest of Italy.

The remainder of this paper is organized as follows. Section 2 provides a brief overview of the most relevant literature while Section 3 explains the data, methodology and econometric models. Section 4 then presents our results and Section 5 offers the conclusion.

## 2. Literature background

Two strands of literature are relevant for our work: (*i*) The strand that links migration and innovation; and (*ii*) the strand that explains IPRs and their relevance.

### *2.1 Migration and Innovation*

In the last two decades, increasing attention has been paid to the economic effects of migration on the destination areas (Nathan 2014) including population growth as well as changes in wage levels and workforce composition both in terms of skills and other demographic variables (Ozgen et al. 2014). The impact of migration on innovation however has received less attention. Recent studies have found a positive relationship between migrants and firm-level innovation (Maré, Fabling, and Stillman 2014; Jonkers 2011). Jensen (2014, 240) highlighted for example that, "people movement is one of the main ways in which tacit knowledge moves between areas." Migrants also act as a circuit breaker for 'group think:' a more diverse group of individuals can reach better innovation outcomes due to the variety of aggregated knowledge (Hong and Page 2004). As such, the inclusion of migrants can benefit the exchange and generation of ideas (Brunow and Stockinger 2013; D'Ambrosio et al. 2019).

Therefore, migration has the potential to change not only demographic composition, but also the skills composition of the labor force in a way that promotes—or hinders—innovative activities. Scholars have mostly focused on the role of high-skilled migrants and so-called STEM migrants (Breschi et al. 2020). For instance, using a survey of college graduates, Faggian and McCann (2009) have shown that regions with high-skilled migration have a higher level of patenting. Bosetti, Cattaneo and Verdolini (2015) also found a positive effect of high-skilled migration on technological and scientific output for 20 European countries.

However, the positive effects of migration on innovation are contested (Venturini, Montobbio, and Fassio 2012). For example, Ortega and Peri (2014) showed, with a sample of 30 OECD countries, that migration had a negative effect on total factor productivity. Recently, Bratti and Conti (2018) found no statistical significance of medium-high and low-skilled international migration on innovation in Italy. They also used patents to measure innovation but complemented them with firm-level survey data to capture non-patented innovation as well.

The negative effects of innovation seem to apply to destination regions that receive a large number of low-skilled migrants. Bratti and Conti (2018) suggested that unskilled migration can reduce social capital, be linked to communication problems among workers, and may even lower incentives for firms to innovate.  Lewis (2011) and Peri (2012) estimated the effect of low-skilled migrants (mainly from Mexico) on US manufacturing industries and found a negative correlation with the use and adoption of new technologies. For Europe, Ozgen, Nijkamp, and Poot (2012) disaggregated foreign immigrants by country of citizenship and found differential effects on innovation performance for 12 European regions, indirectly relating their results to the average skill level of migrants.

Whether or not migration is positively related to innovation is a salient empirical question which needs to be addressed by considering the (potentially opposite) roles of high-skilled and low-skilled migrants. Prior research has dealt more with international migration than with internal migration. This is somewhat at odds with the fact that the scale and long-term impact of internal migration is highly relevant. Internal migration has been characterized by massive movements from rural areas to cities, triggered by educational and employment opportunities, and has supported urbanization, industrialization and post-industrialization (Otoiu, Titan, and Dumitrescu 2014).

This differs from international migration in at least two important aspects. First, the integration of internal migrants tends to be easier, given the common language as well as cultural and institutional proximity (Di Berardino et al. 2019). Second, recent waves of internal mobility mostly concerned higher skilled migrants (Coulombe and Tremblay 2009; Bossavie et al. 2022). For the case of Italy, evidence shows that highly educated individuals move to more industrially-advanced regions (Basile et al. 2019). Such selective migration further widens current regional disparities in human capital endowment.

### *2.2. The Italian context*

Italy has always been characterized by a remarkable North-South divide, which has triggered significant and persistent interregional migration flows where high-skilled workers often move to the more developed Northern regions. Several studies have found that this inflow of highly-educated migrants has further deepened existing regional differences by strengthening the human capital of the host regions (Fratesi and Percoco, 2014), reducing unemployment (Basile et al. 2019) and affecting the quality of institutions (Di Berardino et al. 2019).

In contrast, international migration to Italy has been dominated by low-educated workers (Del Boca and Venturini 2005). In fact, of all European countries, Italy has one of the lowest capacities to attract highly educated immigrants (Organization for Economic Co-operation and Development OECD, 2008). This strong inflow of low-skilled migrants has fed the needs of traditional economic activities which produce labor-intensive goods (Bratti, De Benedictis, and Santoni 2014).

Nonetheless, no study has addressed the impact of the two different types of migration on Italy's level of regional innovation. By including both migration types here, we provide a better understanding of the relationship between migration and innovation across Italian regions. In doing so, we also address the plea for broadening the take on innovation (Bosetti, Cattaneo, and Verdolini 2015).

### *2.3 Measuring innovation beyond patents*

The overwhelming majority of studies on migration and innovation have used patents as the innovation metric. This over-reliance on patent data in the migration and innovation literature (Faggian, Rajbhandari, and Dotzel 2017) is partly due to—until recently—the limited availability of other types of data as well as the general bias of innovation studies towards technological innovation (Castaldi and Mendonça 2022). However, the call for considering a broader range of innovation metrics has already resulted in indexes like the European Regional Innovation Scoreboard (RIS)[1] which includes not only patents, but also trademarks and design applications.

The combination of these three innovation indicators allows for the combined exploitation of the advantages of each metric:

[1] The Regional Innovation Scoreboard (RIS) is the regional extension of the European Innovation Scoreboard (EIS). RIS facilitates a comparative assessment of innovation performance of EU Member States at the regional level (European Commission 2019).

(1) **Patents:** a patent constitutes a "legal right to exclude others from making, using, or selling the patented invention or process for some period of time" (Carlino and Kerr 2015, 7). To be granted a patent for an invention, three main conditions are necessary: novelty, non-obviousness, an industrial application. The last one explains the wide reliance on patents in the manufacturing sector (Greenhalgh and Rogers 2010). Patent statistics can be calculated at different levels of aggregation, including at the regional level (Acs, Anselin, and Varga 2002; Quatraro 2009b). The limits of patents are well known; large firms for example are more likely to use them due to their costs and complexity, hence patent statistics underestimate innovation in small- and medium-sized firms. Additionally, patents provide a wealth of information on how companies position themselves within technological trajectories, although mute later phases of the innovation value chain (Castaldi 2020).

(2) **Trademarks:** a trademark is the right to use symbols (figurative, text or other) to distinctively market a product and signal its quality to consumers. Even though trademark registration does not require any novelty (as patents dVo), a new trademark has to fulfil the main condition of 'distinctiveness' (WIPO 2004). Trademarks are the most widely used IVPR, as they are filed by firms of all sizes and across all economic sectors, partly because of their lower registration costs (Castaldi and Mendonça 2022; Mendonça, Pereira, and Godinho 2004). Trademark-based indicators can therefore help capture innovation in service sectors (Gotsch and Hipp 2012), SME innovation, and non-technological forms of innovation (Flikkema et al. 2019; Flikkema, De Man, and Castaldi 2014). Trademarks also track leading economic indicators at the country (deGrazia, Myers, and Toole 2020) and regional levels (Di Berardino, Onesti, and Pinate, 2020).

(3) **Design rights** are less common than patents and trademarks although they can play an important role in appropriating rents from design and aesthetic innovation (Galindo-Rueda and Millot 2015). A design right essentially protects the visible features of a product (or part

thereof). To register a design, detailed drawings of all the dimensions and characteristics of the product are needed. Data on designs have been exploited in innovation studies only in a few instances (Galindo-Rueda and Millot 2015; Filippetti et al. 2019; Filippetti and D'Ippolito 2017). And while the use of design rights is very common among SMEs (Kitching and Blackburn 1998; Jensen and Webster 2004), the validity of design rights as an innovation metric bears limitations (Filitz, Henkel, and Tether 2015) as most design innovation does not undergo formal registration.

In sum, the three IPRs above can be combined to capture different phases of the innovation process, ranging from invention to design and all the way to commercialization. In fact, firms often exploit their complementarity and file for each IPR in a different innovation phase (Seip et al. 2018). At the same time, this complementarity is much less evident in contexts where organizations are less R&D intensive or where the nature of the innovation is hardly technical (Jensen and Webster 2009). These contexts include low-tech and supplier-dominated or demand-driven manufacturing branches (e.g., consumer goods, fashion) and many service sectors, including knowledge-intensive services (KIS) (Castaldi 2018). In these circumstances, trademarks and designs can help reveal hidden innovation that is not uncovered with patents. From a geographical perspective, combining the three metrics allows us to acknowledge a wider range of regional innovation specializations beyond those based on science and technology (Carree et al. 2015; Capello and Lenzi 2018).

Our overall expectation is to find positive effects of medium- and high-skilled migration flows on innovation, not only for regional patent intensity, but also for trademarks and design rights. This is particularly valuable for countries like Italy with strong creative and design-based sectors, whose innovation activities are poorly captured by patents.

## 3. Data and methods

Econometric analysis is carried out at the Italian province (NUTS3) level by merging data provided by Italy's national statistical office ISTAT on bilateral migration flows by educational level and Eurostat regional data on patent, trademark and design applications. Our panel includes 103 Italian provinces over the period 2003–2012. We opt for NUTS3 level for two main reasons. First, NUTS3 is the most detailed level for which both human capital migration flows and intellectual property rights data are available. Second, several migration studies have used the same scale to measure the effects on innovation (e.g., Bratti and Conti 2018; Crescenzi and Rodríguez-Pose 2011; Niebuhr 2010), hence we can compare our results to previous literature.

### *3.1. Innovation data*

Intellectual Propriety Rights (IPRs) data come from Eurostat: patents come from the European Patent office (EPO) and trademarks and designs from the European Union Intellectual Property Office (EUIPO). Eurostat counts European rather than domestic IPR applications. These international applications are typically higher quality than national ones since their filing is somewhat more complex and costlier.

In the 10-year period considered, Italian provinces have experienced a decrease in patent filings coupled with an increase in the use of trademarks and designs (see Figure 1a). In addition, firms have consistently registered more trademarks than other IPRs.

Although Italy is the second largest European industrial country after Germany, its total factor productivity is rather low due to its reliance on traditional sectors and firms with outdated technology (Quatraro 2009a). Italy also specializes in a number of sectors where creativity and design play a key role (e.g., fashion and architecture). Finally, the Italian economy is dominated by SMEs which partly explains the larger presence of trademarks.

[FIGURE 1 ABOUT HERE]

As the maps in Figure 2 show, similarities exist between the spatial distribution of the three IPRs, as all three are more common in the North and in some of the central provinces. In fact, all top 10 provinces for the three innovation indicators are in the North (see Appendix A.1), while the bottom 10 occur in the South. The top 10 provinces account on average for about 45%, 44% and 49% of all national applications for patents, trademarks and designs. However, the specific rankings vary across innovation indicators, for example with Milan being top for trademarks but not for patents and designs. When considering macro-areas (see Appendix A.2), patent applications have decreased while trademarks and designs increased everywhere with Central and Southern provinces scoring relatively well.

[FIGURE 2 ABOUT HERE]

### *3.2. Migration data*

Provincial level (NUTS3) data come from the Demographic Portal of ISTAT, which classifies migration flows by educational level which includes five categories that range from individuals with no education to individuals with a tertiary education.[2]

We classified migrants into two categories according to their educational level: (i) medium-to high-skilled migrants or those with upper-secondary education or higher and (ii) low-skilled migrants, or those with less than upper secondary education. We opted for these two categories to align our approach to Bratti and Conti (2018) and to ensure that the chosen categories are reasonably populated.

Figure 1b shows the evolution of migration by skills. Foreigners in Italy have, on average, lower levels of education (Ministry of Internal Affairs, 2007). As such, the average share of low-skilled international migrants is about 60% as opposed to 53% for internal flows (see Appendix A.3). Internal migration flows have generally been larger than international

[2] The micro-data dataset on migration was obtained after a specific request to ISTAT, in compliance with legislation on statistical confidentiality and personal data protection.

flows (see Figure 1b) and while international migration has been decreasing over the years, irrespective of skill level, the number of medium- to high-skilled internal migrants has increased.

The maps in Figure 3 illustrate the provincial distribution of medium-to high-skilled versus low-skilled international and internal migrants. While Italy's Northern and Central regions are the preferred destinations for all internal migrants, the picture is less clear for international migrants (Appendix A.4). In fact, international low-skilled migrants are mostly concentrated in the South and North-East, while international medium- to high-skilled migrants are distributed across the whole of Italy.

[FIGURE 3 ABOUT HERE]

### *3.3. Model specification*

To estimate the contribution of migrants on innovation, we rely on a knowledge production functions (KPF) estimation. KPF was first used at the firm level by Griliches (1979) and Hausman, Hall, and Griliches (1984) which was then extended by Jaffe (1986; 1989) to the territorial level. It is now customary in regional innovation studies (Bosetti, Cattaneo, and Verdolini 2015; Bratti and Conti 2018; Gagliardi 2015; Miguélez and Moreno 2012, and others).

Using KPF, we assessed the impact of skill-specific migration inflows on the probability of host provinces to innovate, by estimating the following equation for each of the three IPRs:

$$IPR_{jt} = \beta_0 + \delta_t + \delta_j + \beta_1 mig_{jt-1}^{inter\_medhigh} + \beta_2 mig_{jt-1}^{inter\_low} + \beta_3 mig_{jt-1}^{intra\_medhigh} + \beta_4 mig_{jt-1}^{intra\_low} + \beta_5 rd_{jt-1} + \beta_6 graduates_{j2002} + \beta_n X_{nj} + \mu_{jt} \quad (1)$$

where $j$= 1,2,…,103 indicates the destination province (NUTS3) and $t$ = 2003, 2004,…, 2012 represents the year. The output variables, one for each IPR, are the natural logarithm[3] of

[3] To retain the zeros, we followed a quite common procedure used by Bratti and Conti (2018) and added 0.001 before taking the logarithm.

the innovation indicators (IPRs relative to population, per thousand inhabitants). $mig_{jt-1}$ is our variable of interest which measures the inflow of migration: we distinguish by type and skill level where $mig_{jt-1}^{inter\_medhigh}$ and $mig_{jt-1}^{inter\_low}$ stand for medium- and high-skilled and low-skilled international migrants, while $mig_{jt-1}^{intra\_medhigh}$ and $mig_{jt-1}^{intra\_low}$ stand for medium- and high-skilled and low-skilled intranational migrants (i.e., internal). All migration variables are lagged one year and per thousand inhabitants.

We also include as inputs: $rd_{jt-1}$ , the lagged intramural expenditures in total R&D, both public and private, as a percentage of GDP, and $graduates_{j2002}$ as the share of university graduates over the working-age population as a proxy for human capital. Finally, $X_{nj}$ is a vector of additional *n=1..N* control variables, and $\mu_{i,t}$ is the error term. The regression includes time dummies and region-specific (NUTS2)[4] fixed effects ($\delta_t + \delta_j$). Table 1 provides a description of all variables (correlation matrix plotted in Appendix A.5).

[TABLE 1 AROUND HERE]

The set of control variables accounts for factors expected to be positively related to innovation. These include the logarithm of *population* to measure the size of the province, fixed at one year prior to the estimation to ensure that the variable is not affected by migration flows during the period under analysis (Hunt and Gauthier-Loiselle 2010; Bratti and Conti 2018). Since more internationally-oriented regions should make more use of IPRs (Mendonça, Pereira, and Godinho 2004), we also control for the degree of openness of a province (*open*), computed as the sum of import and export in Euros over GDP (Ariu, Docquier, and Squicciarini 2016; Di Berardino et al. 2019).

[4] Since we have a short time interval ($\delta_t$) and differences in migration flows between provinces are quite persistent, NUTS3 fixed effects could not be included. This problem was also emphasized by Niebuhr (2010). We opt for using fixed NUTS2 ($\delta_j$) effects, capturing regional differences, instead of provincial ones (Bratti and Conti 2018; Bratti, De Benedictis, and Santoni 2014; Wagner, Head, and Ries 2002). Bratti and Conti (2018) considered this intermediate approach to be particularly effective for the case of Italy.

We further control for the spatial agglomeration of industries by including the degree of district intensity of provinces (*i-district*) (Di Berardino et al. 2016) as the share of employees in industries that belong to an industrial district (ID) over the industry total employment. This variable is important as there is evidence in Italy that firms within industrial districts innovate more (see Muscio 2006; Cainelli and De Liso 2005; Capasso and Morrison 2013).

The overall regional industrial structure also matters, since the degree and type of innovation differ across industries (Klevorick et al. 1995). We follow Niebuhr (2010) and include the ratio of manufacturing (lagged) to service employment (*sectoral*). We then include a control on the *firm-size* composition (the share of manufacturing employees in SMEs and large firms over total employment). Finally, we also control the composition by technological intensity, distinguishing economic activities according to the Eurostat 2-digit sectoral classification of *High-tech* manufacturing industry (the share of employees on high-tech, medium high-tech, medium low-tech and low-tech) and *Knowledge-Intensive* service (the share of employees on KIS and less knowledge-intensive services or LKIS).

***3.4. Instrumental variables***

Since the decision whether and where to move is often based on expectations regarding growth prospects (Gagliardi 2015; Shen and Liu 2016), the use of an instrumental variable (IV) is necessary to control for exogenous sources of variation in the local supply of the destination regions (Fratesi and Percoco 2014; Niebuhr 2010). Methodologically, the potential endogeneity bias is a challenge. In some provinces, the correlation between migration and innovation may not occur as result of 'genuine causality,' but rather as a mere implication of settlement patterns (Gagliardi 2015). Moreover, there might be self-selection and reverse causality. In fact, Kazakis (2019) shows that more productive and innovative regions in the United States are more likely to attract human capital, and at the same time, regions that attract more human capital tend to be more innovative and exhibit higher levels of productivity. To address this issue, we follow the strategy used by several other scholars (e.g., Gagliardi 2015; Bratti and Conti 2018) of including fixed effects (as in equation [1]) and instrumental variables (two-stage least squares 2SLS) to control for endogeneity.

The source of endogeneity of the migration variables is the adjustment in the local labor markets to migration flows (Fratesi and Percoco 2014), which in turn induces economic growth and increased productivity because of the development of new knowledge and innovation (in our case regional IPRs). To build our instruments, we used a variant of Card (2001). The approach is based on the idea that migration is path dependent and thus the initial share of migrants can be used as a predictor for subsequent inflows. The work by Card has been used extensively in the literature to measure the effect of international migration (e.g., Hunt and Gauthier-Loiselle, 2010; Kerr and Lincoln, 2010; Ortega and Peri, 2014), but less so for internal migration, with the exception of Fratesi and Percoco (2014) who constructed a similar instrument to measure the effect of interregional migration on regional growth in Italy.

Hence, our 'predicted' stock of international migrants by skill *s*, in province *j* and year *t* is:

$$ivMig_{jt}^{inter,s} = \sigma_{2002}^{inter,s} \frac{Mig_t^{inter,s}}{pop_{jt}} \quad \text{where} \quad \sigma_{2002}^{inter,s} = \frac{Mig_{j2002}^{inter,s}}{Mig_{2002}^{inter,s}} \qquad (2)$$

where $Mig_t^{inter,s}$ is the total number of international migrants with skill *s* (medium- and high or low) moving to Italy at time *t*; $pop_{jt}$ is the population of the destination province *j* at time; and $\sigma_{2002}^{inter,s}$ is the share of international migrants with skill *s* that moved to province *j* over the total number of international migrants with skill *s* moving to Italy in 2002, a year preceding the estimation period.

Similarly, the 'predicted' stock of internal migrants by skill *s*, in province *j* and year *t* is:

$$ivMig_{jt}^{intra,s} = \sigma_{2002}^{intra,s} \frac{Mig_t^{intra,s}}{pop_{jt}} \quad \text{where} \quad \sigma_{2002}^{intra,s} = \frac{Mig_{j2002}^{intra,s}}{Mig_{2002}^{intra,s}} \qquad (3)$$

Considering the effects by migrant type as well as skill level has the potential advantage of capturing differences in settlement patterns. There is a geographical variation in the destination of international and internal migration, as we saw in the analysis of flows in Section 3.2; employment expectations between foreign and Italian employees might also be different. In fact, the occupations where foreign workers operate are concentrated within a limited number of economic activities.[5] The correlation between the initial fractions of migrants and the subsequent inflow at the provincial level confirms the 'predicted' effect.[6]

Admittedly, the instruments might not be fully exogenous, as migrants—especially interregional migrants—might have partly decided their location based on unobserved variables that are correlated with innovation. For relevance, reliable instruments need to be correlated with the regressors , while also being orthogonal to the error term for validity (Orefice 2010). The F-stat of joint significance of the instruments in the first stage regression shows that our instruments are indeed not weak, and are therefore relevant. The results are reported in Appendix A.7, where a series of other alternative tests are presented (Cragg-Donald Wald *F* statistic, Kleinberg-Paap rk Wald *F* statistic and Stock and Yogo critical values).[7] As for validity, we cannot directly use the overidentification restrictions (Hansen J test) because the equations are exactly identified. To provide a formal test, we relied on the added surely orthogonal instruments, as done in Orefice (2010) (see Appendix A.8). In the Hansen robustness check test, the null hypothesis of exogeneity of the instruments could not be rejected, so we conclude that our instruments are valid.

[5] Foreign workers, mainly operating in industry (particularly construction), the accommodation sector and family services, have an altogether modest presence in sectors in which Italians are widely employed such as: IT, research and development, and business services (1st Report on Immigrants in Italy, 2007).

[6] The pairwise correlations between the instruments and the migrations are above 0.83.

[7] The Cragg-Donald F statistic (and its robust analog, i.e., rk Wald statistic) is compared to tabulated Stock and Yogo (2005) critical values.

## 4. Estimation results

### *4.1 Main models*

We first estimated equation (1) for each IPR with OLS (Appendix A.6) and then with 2SLS (Table 2). The OLS results show a similar effect of migration on both patents and designs, where larger internal migration flows of individuals with medium to high skills are positively correlated with both IPRs, while low-skilled negatively so. As for trademarks, international migration is positively associated, but only if migrants have at least upper-secondary education. Nevertheless, the endogeneity test[8] (see Appendix A.6) provides sufficient evidence to reject the null hypothesis of exogeneity of our regressor (Baum, Schaffer, and Stillman 2016), indicating that OLS is not consistent.

[TABLE 2 AROUND HERE]

The 2SLS estimates for patents are displayed in Table 2 (columns 1a-c). Results show that provinces with a higher ability to attract skilled migrants from other Italian provinces have the best performance in terms of applications (significant at 1%). Instead, low-skilled internal migration is significantly negatively associated with provincial patenting. This result is in line with the mechanisms suggested by the theory: low-skilled migration reduces incentives for technological invention. On the other side, the inflows of medium- to high-skilled international migrants correlate with patent applications (at 5%), but negatively so. This result sheds new light on the consequences of knowledge and skill complementarities between both types of migration on the local economy. Although the negative implications of medium- to high-skilled migration are less obvious than the positive, our study is not the first to find such evidence (Behrens and Sato 2011; Faggian, Rajbhandari, and Dotzel 2017; Schlitte 2012). The negative

[8] For the models explaining design intensity, endogeneity tests fail to reject the null hypothesis. Demko (2012) pointed out that, even in the case of strong instruments, weak correlations between the instrument and the error term are not always rejected. To cope with this, we also provide estimations using a Limited Information Maximum Likelihood estimator (or LIML) for designs. LIML estimation is more reliable than the IV estimator when instruments are many or weak in correlations with the error term (Bascle 2008; Murray 2017). The LIML model confirms the results obtained with the 2SLS (see Appendix A.9).

relation can be explained with the lower barriers that intra-national migrants face when moving to a new destination inside the same country of residence (Holmes et al. 2000; Di Berardino et al. 2019). Cultural background differences might stand in the way of absorbing international migrants' knowledge and skills (Bosetti, Cattaneo, and Verdolini 2015; Niebuhr 2010; Østergaard, Timmermans, and Kristinsson 2011). In the Italian context, there is also evidence that because the educational qualifications of foreign migrants is often not recognized, they are confined to low-skilled jobs (Bonifazi 2007; Ministry of Internal Affairs 2007; Reyneri 2006).

The control variables results are mostly in line with previous literature. Patent activity is positively correlated with R&D expenditures and a higher endowment of university graduates. Larger provinces patent more, and their degree of trade openness also matters. The regional specialization in manufacturing and the presence of large firms in the regional economic landscape are also positively associated with patenting, as a dominance of medium- and high-tech and low-tech industries.

As for trademarks (Table 2, columns 2a-c), the results paint a picture where only internal inflows of medium- and high-skilled migrants positively influence the performance of trademarks, while low-skilled migrants are insignificant. Among the control variables, the intensity of applications is positively associated with population size and R&D expenditures. This might seem counterintuitive, but R&D-intensive firms can leverage trademarks in the downstream phase of the innovation process (Flikkema, De Man, and Castaldi 2014). The degree of openness of the local economy is not significant, a result somewhat surprising as internationally-oriented firms should, in principle, make more use of trademarks (Mendonça, Pereira, and Godinho 2004). Regional specialization appears statistically significant (column 2a) with a positive association with both large and small and medium manufacturing firms (column 2b). Specifically, provinces with a stronger presence of low-tech industries (column 2c) have higher trademark intensities, which is in line with Millot (2009). Not surprisingly, the industrial district variable also shows a positive association, since industrial districts in Italy are predominantly characterized by traditional low-tech activities such as textiles, fashion, leather and related products.

Finally, the results on designs (Table 2, columns 3a-c) show an effect for internal migration in line with those of patents, in which larger inflows of individuals with medium-high (low) skills positively (negatively) correlated with design intensity. Among the controls, population size and the regional specialization in manufacturing are positively and significantly associated with design intensity. The size of firms matters, and provinces with a large share of SME industries show higher intensity in the use of design rights, in line with Jensen and Webster's (2006) finding that SMEs make more use of design rights. There are also statistically significant differences in design applications between provinces specialized in sectors of different technological intensity. In particular, provinces with a higher share of employees in medium-low-tech and low-tech industries (column 3c) have higher design intensities. The share of KIS is negatively associated with designs, even though only at a 10% significance level. This is at odds with the evidence that these services are users of design rights (Kitching and Blackburn 1998; Jensen and Webster 2006), but might also have to do with the limited degree of maturity of KIS in the Italian case, as compared to other European countries (Di Berardino and Onesti, 2020).

While the 2SLS estimations tend to confirm OLS, the coefficients are larger in magnitude (see Table 2 and Appendix A.6). We can assume that our IV model is correcting for some unobserved variables that are negatively correlated with our observables (migration flows) and the outcome variable (innovation). For example, unobserved regional policies could influence migration decisions (e.g., Bertocchi and Strozzi 2008; Nifo and Vecchione 2014) and foster regional innovation (e.g., D'Ingiullo and Evangelista 2020; Rodriguez-Pose and di Cataldo 2015). This might lead to underestimated coefficients in a simpler OLS model.

The IV estimations are robust to a number of robustness checks (see Appendix A.7). The F-statistics are always significant (p-val. 0.000) and well above the threshold value of 10. The Kleinberg-Paap rk Wald *F*-statistic also appears above all critical values of Stock and Yogo (2005), proving our instruments are strong.

### *4.2. Territorial decomposition*

The aggregated picture may hide divergent paths of the different macro-areas. Existing literature shows how the role of migration may vary between regions with substantial socio-economic and institutional differences (Quatraro 2009a; Fratesi and Percoco 2014; Rodriguez-Pose and Di Cataldo 2015). The high territorial heterogeneity of Italy, with highly dynamic as well as economically lagging regions, led us to investigate the effects of migration on innovation by grouping the provinces into two geographical macro-areas: North and Central-South. It is important to note that the macro-territorial analysis is conducted by distinguishing the Central-South from the North to avoid emphasizing cases where the absolute values of innovation and migration are very low.

The results of the 2SLS regressions for the two macro-areas are presented in Table 3. For patents, the positive association of medium- and high-skilled internal migrants is in line with the aggregate results for both macro-areas. While the negative effects of migrants (low and medium- to high-skilled, both internal and international), are limited to the Central and Southern provinces. As for trademarks, the models for Central-South explain very well the differences in the intensities across provinces; this result is somewhat expected considering the increase in applications (see b, Appendix A.2). The results for design reveal a significant relationship between all types of migration, but is limited to the Northern provinces. This suggests an early use by companies in Northern regions, that already used other intellectual property such as patents and trademarks (see Appendix A.1).

[TABLE 3 AROUND HERE]

### *4.3 Summary of key results*

Our significant results are summarized in Table 4 where each column corresponds to the final models (column c of Table 2) and standardized coefficient estimates are bracketed. Standardized coefficients allow the comparison of effect sizes; we take the exponential value given that our dependent variables are in log. Each estimated value can be interpreted as the increase or decrease in the respective IPR intensity associated with a one standard deviation increase of the different types of migration. For example: a one standard deviation increase in medium- and high-skilled internal migration comes with a 19.5% increase in trademark intensity at the province level.[9]

[TABLE 4 AROUND HERE]

The table clearly shows that, for our sample, internal migration—as opposed to international—is mostly related to innovation. When comparing the coefficients of the relations for internal migration, the positive association of medium and high-skilled migration with all three innovation proxies is stronger than the negative association of low-skilled migration. The latter is only found for patent and design intensity, while trademark intensity it is not significant. As these results have implications for research and policy, we discuss each in the final section.

## 5. Conclusions

This paper closely examined the potential effect of migration on regional innovation in Italy. Our specific aim was to shed new light on the relationship between skill-specific international and internal migration flows and regional innovation, by capturing broader indicators than just patents.

The empirical analysis was carried out at the Italian province level (NUTS3), using an IV-2SLS approach on a 2003–2012 dataset. The first study to consider both international and

[9] For medium- and high-skilled international migration it's safe to said that one standard deviation comes with 19.3% decrease in patent intensity.

internal migration flows, our results allowed us to empirically assess which migration types matter for innovation.

Our study has four key results. First, Italian provinces with a greater share of medium- and high-skilled migrants has a higher intensity of all three IPRs used as innovation metrics. In contrast, low-skilled migration has a negative relationship with innovation. This general result aligns with the literature and provides fresh evidence for the idea that medium- and high-skilled migration can be a valuable source of knowledge and talent, with effects stretching to different types of innovation and different sectors. Second, and contrary to the results of internal migration, international migration is only significantly—and negatively—associated with patents. Third, the suite of innovation metrics needs to be broadened so the nuanced relationship between migration and innovation can be captured. Finally, and as we expected given the historical territorial dualism of Italy and the geographical concentration of innovation activity, we found the relation of internal migration and innovation to be different by macro-area.

By providing a more detailed picture of the relationship between migration and innovation, our study can help policy makers develop and monitor their migration policies to foster local innovation. This can be particularly important in countries such as Italy characterized by a territorial dualism. The Italian innovation gap also appeared strong when using non-patent metrics; this insight might also help to devise ‘distributed development’ policies (Iammarino, Rodriguez-Pose, and Storper 2019) that are sensitive to the quality of local specializations. Our empirical approach can additionally help to assess regional migration policy strategies, given the availability of the three IPRs in the European Regional Innovation Scoreboard (RIS) and the regionalized trademark and design data now being made available from the European Office for Intellectual Property (EUIPO).

Although this study represents a step forward in the migration and innovation literature, it has some limitations. However, these limitations also represent opportunities for further research. First, the same analysis could be repeated using firm-level data instead of aggregated provincial data. This could validate our measures and results by comparing them to primary data collected by way of firm surveys, shedding light on the suggested mechanisms behind aggregate relations and for instance, on whether migration really increases knowledge diversity. At the same time, firm-level data would also account for firm size and could thus better capture the differences in IPR use.

Second, and from an econometric point of view, the instrumental strategy could be further improved with the identification of new variables correlated with migration (both international and internal). Also, future research could strengthen the empirical strategy to capture migrant skill composition to possibly add novel elements, including a gender composition.

Third, we have treated the three IPRs as separate indicators, yet one could also combine them, as they have high degrees of complementarity (Grazzi, Piccardo, and Vergari 2020; EUIPO 2020). Additionally, one could try to account for the fact that IPRs are highly heterogenous in value, with some patents or trademarks representing innovation with a much stronger economic impact. For patents, several indicators of value exist (Higham, de Rassenfosse, and Jaffe 2021) and have been leveraged at the regional level as well (Castaldi, Frenken, and Los 2015; Miguelez and Moreno 2018). Trademark value indicators also exist (Nasirov 2020) but have hardly been used in regional empirical research, while no proxy for the value of design rights exists. This could be developed, starting from those, for trademarks.

Finally, despite the usefulness of combining international and internal migration data, the Italian context is one in which international migration is much smaller in size. As such, our estimations could be replicated for countries that have experienced a different weight of the two migration flows. Still, our main message for scholars and policymakers would remain the same:

to understand the relationship between migration and innovation, it is worthwhile to consider both international and internal migration flows.

**Disclosure statement**

No potential conflict of interest was reported by the authors.

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Table 1. List of indicators at provincial level used in the estimations and descriptive statistics

Table 2. Estimations on patents, trademarks and designs: 2SLS results

Table 3. Macro-territorial estimations

Table 4. Summary of key significant relations between migration and innovation proxies

Table 1. List of indicators at provincial level used in the estimations and descriptive statistics

| Variable | Code | Description | Obs. | Mean | SD |
|---|---|---|---|---|---|
| **Dependent variables** | | | | | |
| Patent | | natural logarithm of number of patent applications per 1000 inhabitants | 1030 | -3.317 | 1.300 |
| Trademark | | natural logarithm of number of trademark applications per 1000 inhabitants | 1030 | -3.093 | 1.328 |
| Design | | natural logarithm of number of design applications per 1000 inhabitants | 1030 | -4.409 | 1.422 |
| **Explanatory variables** | | | | | |
| International migration | $mig^{inter\_medhigh}$ | number of international migrants with at least upper-secondary education per 1000 inhabitants | 1030 | 0.237 | 0.125 |
| | $mig^{inter\_low}$ | number of international migrants with lower than upper-secondary education per 1000 inhabitants | 1030 | 0.407 | 0.282 |
| Intranational migration | $mig^{intra\_medhigh}$ | number of intranational (i.e., internal) migrants with at least upper-secondary education per 1000 inhab. | 1030 | 3.804 | 1.300 |
| | $mig^{intra\_low}$ | number of intranational migrants with lower than upper-secondary education per 1000 inhabitants | 1030 | 4.644 | 1.605 |
| *Innovation inputs* | | | | | |
| Research and Development | rd | share of the intramural R&D total expenditure euros, weighted by patents of each NUTS3 within the NUTS2, over million GDP | 1030 | 0.414 | 0.582 |
| Human Capital | graduates | share of the number of in course university graduates, weighted by the number of campuses per province, over population 18-64 (2002) | 1030 | 0.122 | 0.216 |
| **Control variables** | | | | | |
| Population | ln_pop | natural logarithm of number of inhabitants (2002) | 1030 | 12.899 | 0.698 |
| Degree of openness | open | share of import and export over GDP | 1030 | 38.574 | 29.970 |
| Degree of district intensity | i-district | share of employment continuous variable that ranges between zero (no employee in the province works in an ID-related sector) and one (the workers are employed in firms belonging to IDs) (2001 census) | 1030 | 0.298 | 0.361 |
| Sectoral composition | sectoral | share of manufacturing to service employment | 1030 | 29.654 | 14.816 |
| Company size | sme | share of employment in SMEs manufacturing industries (1–249 employees) on the total employment | 1030 | 47.850 | 12.476 |
| | large | share of employment in large manufacturing industries (>250 employees) over total employment | 1030 | 6.227 | 4.754 |
| Classification Manufacturing | high-tech | share of employees in High-tech over the total of employment | 1030 | 1.082 | 1.657 |
| | med-high-tech | share of employment in Medium-high-tech over total employment | 1030 | 5.374 | 4.133 |
| | med-low-tech | share of employment in Medium-high-tech over total employment | 1030 | 8.115 | 3.583 |
| | low-tech | share of employees in Low-tech over total employment | 1030 | 10.962 | 6.192 |
| Classification Services | kis | share of employment in Knowledge-intensive services (KIS) over total employment | 1030 | 19.912 | 4.694 |
| | lkis | share of employment in Less knowledge-intensive services (LKIS) over total employment | 1030 | 40.973 | 7.463 |

*Notes*: The reported values correspond to the estimation period 2003-2012. The *population, graduates* and *district intensity* variables enter the model fixed. All the other variables enter the model lagged one period.

Table 2. Estimations on patents, trademarks and designs: 2SLS results

| | Patent | | | Trademark | | | Design | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1a) | (1b) | (1c) | (2a) | (2b) | (2c) | (3a) | (3b) | (3c) |
| $mig^{inter\_medhigh}$ | -1.729*** | -1.758*** | -1.646** | 0.731 | 1.334 | 0.679 | -1.313 | -0.017 | -0.443 |
| | [0.637] | [0.681] | [0.688] | [0.886] | [0.945] | [0.942] | [0.922] | [0.936] | [1.005] |
| $mig^{inter\_low}$ | 0.458* | 0.463* | 0.412 | -0.133 | -0.374 | -0.119 | 0.485 | 0.100 | 0.225 |
| | [0.259] | [0.269] | [0.277] | [0.366] | [0.379] | [0.389] | [0.373] | [0.383] | [0.407] |
| $mig^{intra\_medhigh}$ | 0.225*** | 0.175*** | 0.197*** | 0.192*** | 0.169*** | 0.178*** | 0.342*** | 0.247*** | 0.299*** |
| | [0.041] | [0.041] | [0.041] | [0.055] | [0.055] | [0.055] | [0.058] | [0.058] | [0.056] |
| $mig^{intra\_low}$ | -0.089*** | -0.047* | -0.079*** | -0.058 | -0.032 | -0.041 | -0.158*** | -0.096** | -0.079** |
| | [0.025] | [0.026] | [0.026] | [0.037] | [0.037] | [0.037] | [0.040] | [0.040] | [0.038] |
| rd | 0.302*** | 0.361*** | 0.325*** | 0.293*** | 0.301*** | 0.321*** | 0.102 | 0.189* | 0.155 |
| | [0.084] | [0.092] | [0.088] | [0.083] | [0.078] | [0.081] | [0.120] | [0.105] | [0.119] |
| graduates $_{2002}$ | 0.434*** | 0.311*** | 0.330*** | 0.099 | 0.055 | 0.131 | -0.101 | -0.204 | -0.067 |
| | [0.077] | [0.081] | [0.073] | [0.106] | [0.103] | [0.104] | [0.133] | [0.134] | [0.132] |
| ln_pop $_{2002}$ | 0.497*** | 0.475*** | 0.466*** | 0.589*** | 0.582*** | 0.618*** | 0.533*** | 0.570*** | 0.687*** |
| | [0.037] | [0.040] | [0.040] | [0.055] | [0.056] | [0.056] | [0.062] | [0.062] | [0.066] |
| open | 0.002** | 0.002** | 0.002** | 0.000 | 0.000 | 0.001 | -0.003*** | -0.002*** | -0.003*** |
| | [0.001] | [0.001] | [0.001] | [0.001] | [0.001] | [0.001] | [0.001] | [0.001] | [0.001] |
| i-district | -0.139** | 0.242*** | 0.044 | 0.570*** | 0.652*** | 0.417*** | 0.489*** | 0.750*** | 0.442*** |
| | [0.068] | [0.064] | [0.072] | [0.092] | [0.085] | [0.093] | [0.124] | [0.122] | [0.135] |
| *share of employment* | | | | | | | | | |
| sectoral | 0.016*** | | | 0.008*** | | | 0.019*** | | |
| | [0.002] | | | [0.003] | | | [0.003] | | |
| sme-size | | 0.005 | | | 0.013*** | | | 0.019*** | |
| | | [0.003] | | | [0.004] | | | [0.004] | |
| large-size | | 0.028*** | | | 0.027*** | | | 0.013 | |
| | | [0.005] | | | [0.007] | | | [0.009] | |
| med-high-tech | | | 0.039*** | | | -0.009 | | | -0.034*** |
| | | | [0.006] | | | [0.008] | | | [0.010] |
| med-low-tech | | | 0.012 | | | 0.004 | | | 0.071*** |
| | | | [0.008] | | | [0.009] | | | [0.011] |
| low-tech | | | 0.017*** | | | 0.028*** | | | 0.022*** |
| | | | [0.004] | | | [0.006] | | | [0.007] |
| kis service | | | 0.000 | | | 0.004 | | | -0.014* |
| | | | [0.006] | | | [0.008] | | | [0.008] |
| costant | -9.715*** | -9.483*** | -9.388*** | -11.532*** | -12.094*** | -11.948*** | -12.209*** | -13.255*** | -14.358*** |
| | [0.505] | [0.574] | [0.566] | [0.745] | [0.774] | [0.793] | [0.875] | [0.901] | [0.945] |
| Observations | 1,030 | 1,030 | 1,030 | 1,030 | 1,030 | 1,030 | 1,030 | 1,030 | 1,030 |
| R-squared | 0.846 | 0.843 | 0.847 | 0.734 | 0.738 | 0.739 | 0.714 | 0.712 | 0.722 |
| Endog. test [a] | | | | | | | | | |
| *p*-value | 0.001 | 0.001 | 0.001 | 0.046 | 0.039 | 0.036 | 0.562 | 0.942 | 0.985 |

*Notes*: The dependent variables are the log of *patent, trademark* and *design* applications per 1000 inhabitants at province level (NUTS-3) for Italy, 2003-2012. See Table 1 for variables definition. All models include year and region NUTS2 fixed effects. Standard errors are in bracket and robust to heteroskedasticity. Statistically significant a: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The omitted categories (high-tech and LKIS) are considered the most innovative and the least innovative sectors, respectively.

[a] The F-test of the first-stage, the Wald F statistic and the Stock and Yogo critical values of the estimations are plot on Appendix A.7.

Table 3. Macro-territorial estimations

| | North | | | Centre-South | | |
|---|---|---|---|---|---|---|
| | (1a) | (1b) | (1c) | (2a) | (2b) | (2c) |
| **Patent** | | | | | | |
| $mig^{inter\_medhigh}$ | -0.132 | 0.598 | 0.469 | -2.656* | -2.493 | -2.080* |
| | [0.511] | [0.666] | [0.716] | [1.595] | [1.617] | [1.458] |
| $mig^{inter\_low}$ | -0.489 | -0.949** | -0.645 | 0.763 | 0.645 | 0.542 |
| | [0.375] | [0.430] | [0.479] | [0.527] | [0.546] | [0.493] |
| $mig^{intra\_medhigh}$ | 0.141*** | 0.094*** | 0.137*** | 0.366*** | 0.322*** | 0.386*** |
| | [0.033] | [0.036] | [0.033] | [0.129] | [0.111] | [0.118] |
| $mig^{intra\_low}$ | -0.045* | 0.001 | -0.036 | -0.215*** | -0.210*** | -0.250*** |
| | [0.024] | [0.027] | [0.023] | [0.068] | [0.063] | [0.063] |
| **Trademark** | | | | | | |
| $mig^{inter\_medhigh}$ | 1.324* | 2.061** | 1.427 | -3.903* | -1.159 | -3.695* |
| | [0.751] | [1.049] | [1.111] | [2.327] | [2.303] | [2.116] |
| $mig^{inter\_low}$ | 0.389 | -0.096 | 0.294 | 1.300 | 0.414 | 1.210 |
| | [0.540] | [0.627] | [0.765] | [0.791] | [0.795] | [0.737] |
| $mig^{intra\_medhigh}$ | 0.086* | 0.088 | 0.107** | 0.687*** | 0.485*** | 0.658*** |
| | [0.052] | [0.054] | [0.050] | [0.164] | [0.145] | [0.166] |
| $mig^{intra\_low}$ | 0.013 | 0.036 | 0.027 | -0.361*** | -0.268*** | -0.316*** |
| | [0.039] | [0.041] | [0.037] | [0.097] | [0.086] | [0.093] |
| **Design** | | | | | | |
| $mig^{inter\_medhigh}$ | -6.296*** | -4.753*** | -5.639*** | -2.470 | -0.121 | -3.639 |
| | [1.332] | [1.639] | [1.726] | [2.115] | [2.197] | [2.013] |
| $mig^{inter\_low}$ | 5.168*** | 4.582*** | 4.946*** | 0.514 | -0.283 | 0.876 |
| | [0.939] | [1.075] | [1.189] | [0.716] | [0.768] | [0.702] |
| $mig^{intra\_medhigh}$ | 0.560*** | 0.463*** | 0.522*** | 0.272* | 0.004 | 0.204 |
| | [0.072] | [0.076] | [0.068] | [0.149] | [0.142] | [0.142] |
| $mig^{intra\_low}$ | -0.173*** | -0.142** | -0.123** | -0.213*** | -0.102 | -0.118 |
| | [0.052] | [0.057] | [0.050] | [0.082] | [0.080] | [0.079] |
| Observations | 460 | 460 | 460 | 570 | 570 | 570 |

*Notes*: The dependent variable is the log of *patent, trademark and design* applications per 1000 inhabitants at province level (NUTS-3) for Italy, 2003-2012. The full models are displayed in the Appendix A.10-12. See Table 1 for variables definition. All models include year and region NUTS2 fixed effects. Standard errors are in bracket and robust to heteroskedasticity. Statistically significant a: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4. Summary of key relationships between migration and innovation proxies

| | **Patent intensity** (1c) | **Trademark intensity** (2c) | **Design intensity** (3c) |
|---|---|---|---|
| $mig^{inter\_medhigh}$ | *negative*** [0.193] | | |
| $mig^{inter\_low}$ | | | |
| $mig^{intra\_medhigh}$ | *positive**** [1.218] | *positive**** [1.195] | *positive**** [1.348] |
| $mig^{intra\_low}$ | *negative**** [0.924] | | *negative*** [0.924] |

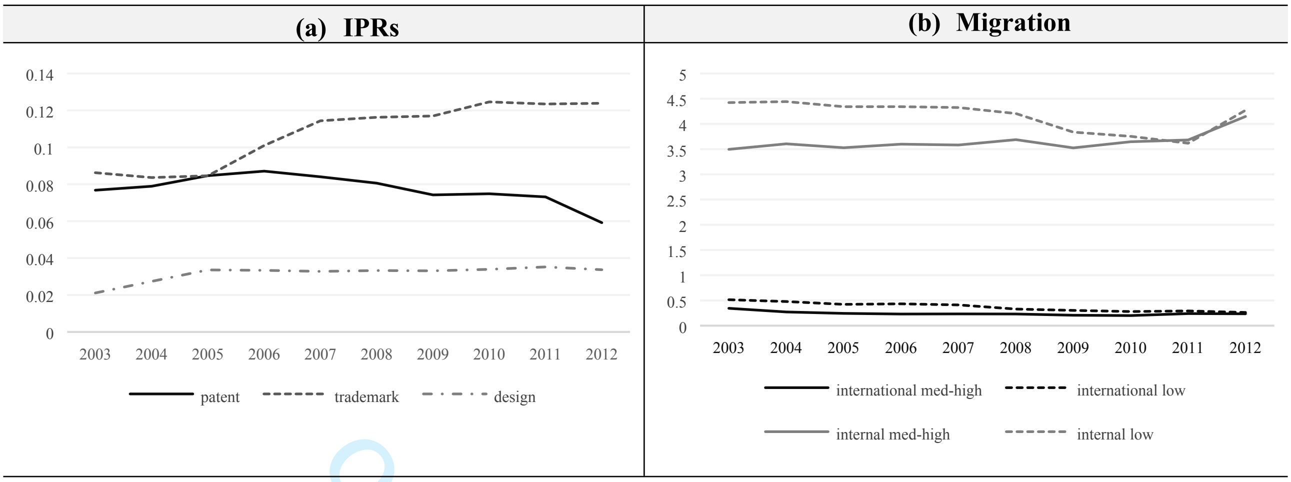
*Notes*: The numbers in brackets are the exponential values of the standardized coefficients from the full models, i.e., columns [c] of Table 2. Statistically significant a: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure 1. Intellectual propriety rights applications and migration dynamics in Italy

Figure 2. Intellectual propriety rights applications at provincial level in Italy

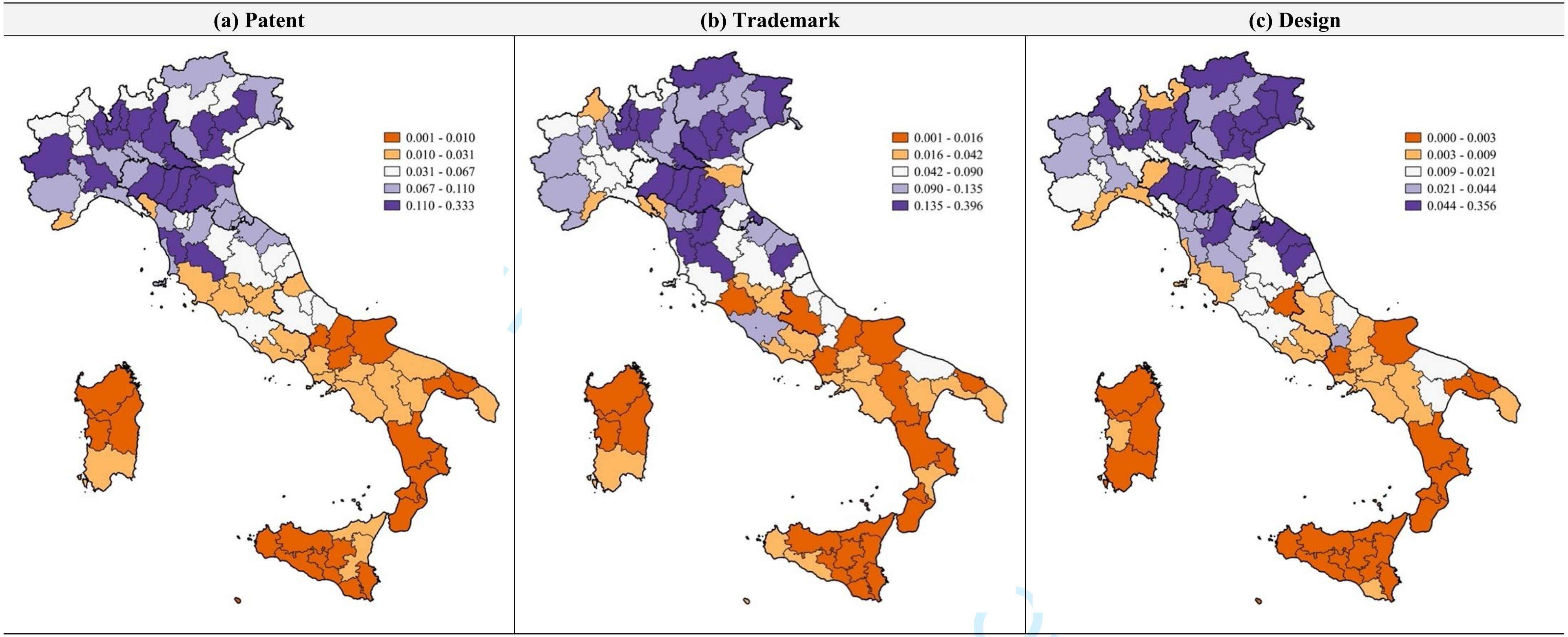
Figure 3. International and internal migration by skill level at provincial level in Italy

Figure 1. Intellectual propriety rights applications and migration dynamics in Italy



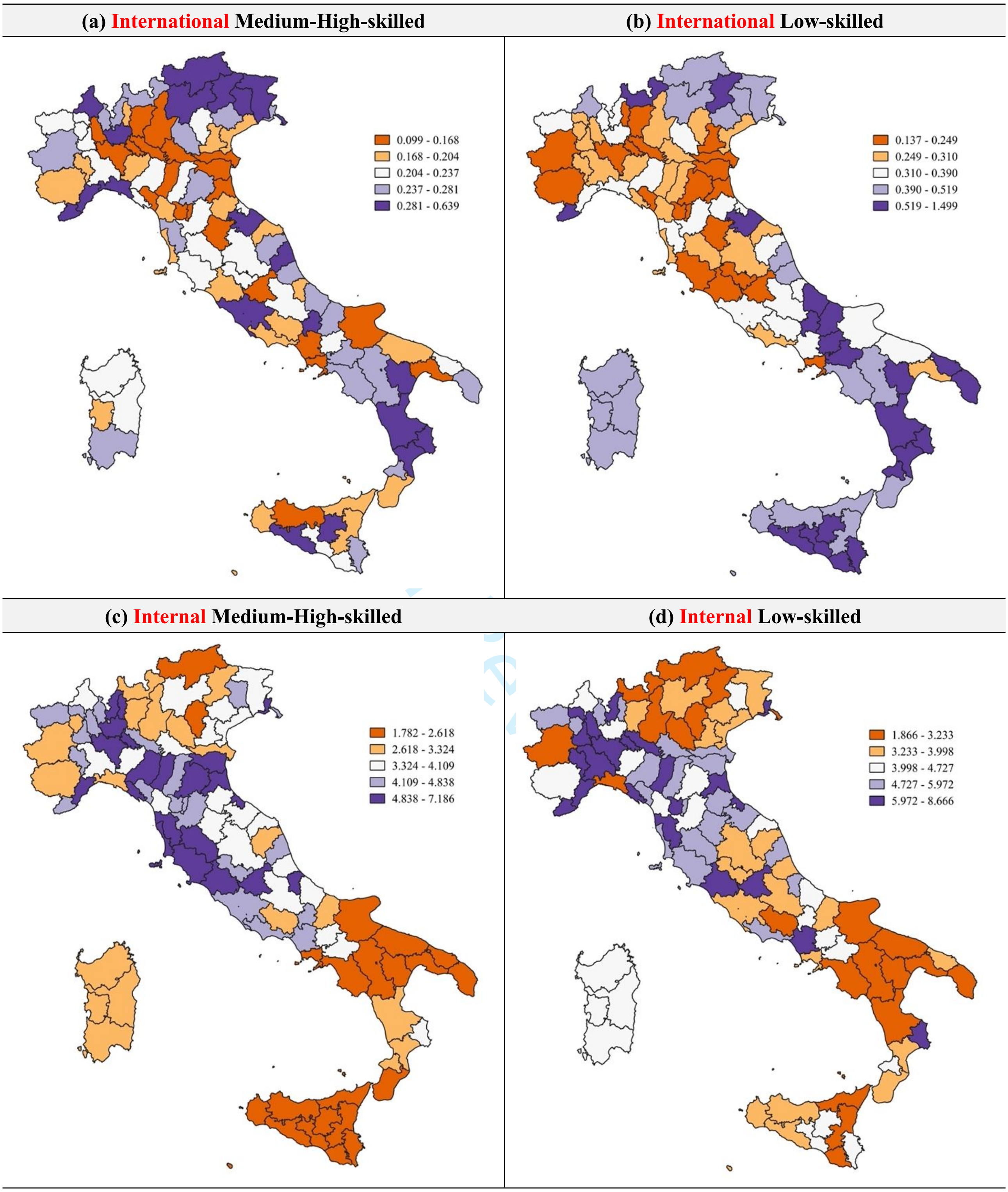

*Notes*: The data correspond to the period 2003-2012 (a) *patent*, *trademark* and *design* applications per 1000 inhabitants; (b) medium- and high-skilled and low-skilled international and internal migrants per 1000 inhabitants.

Figure 2. Intellectual propriety rights applications at provincial level in Italy




*Notes*: The data correspond to averages over the period 2003-2012 -equal quantiles-. IPRs by Italian macro-regions from 2003-2012, where the 2003 = 100. (a) *patent* applications per 1000 inhabitants; (b) *trademark* applications per 1000 inhabitants; (c) *design* applications per 1000 inhabitants.

Figure 3. International and internal migration by skill level at provincial level in Italy




*Note*: The data correspond to averages over the period 2003-2012 -equal quantiles-. (a) medium- and high-skilled international migrants per 1000 inhabitants; (b) low-skilled international migrants per 1000 inhabitants; (c) medium- and high-skilled internal migrants per 1000 inhabitants; (d) low-skilled internal migrants per 1000 inhabitants.

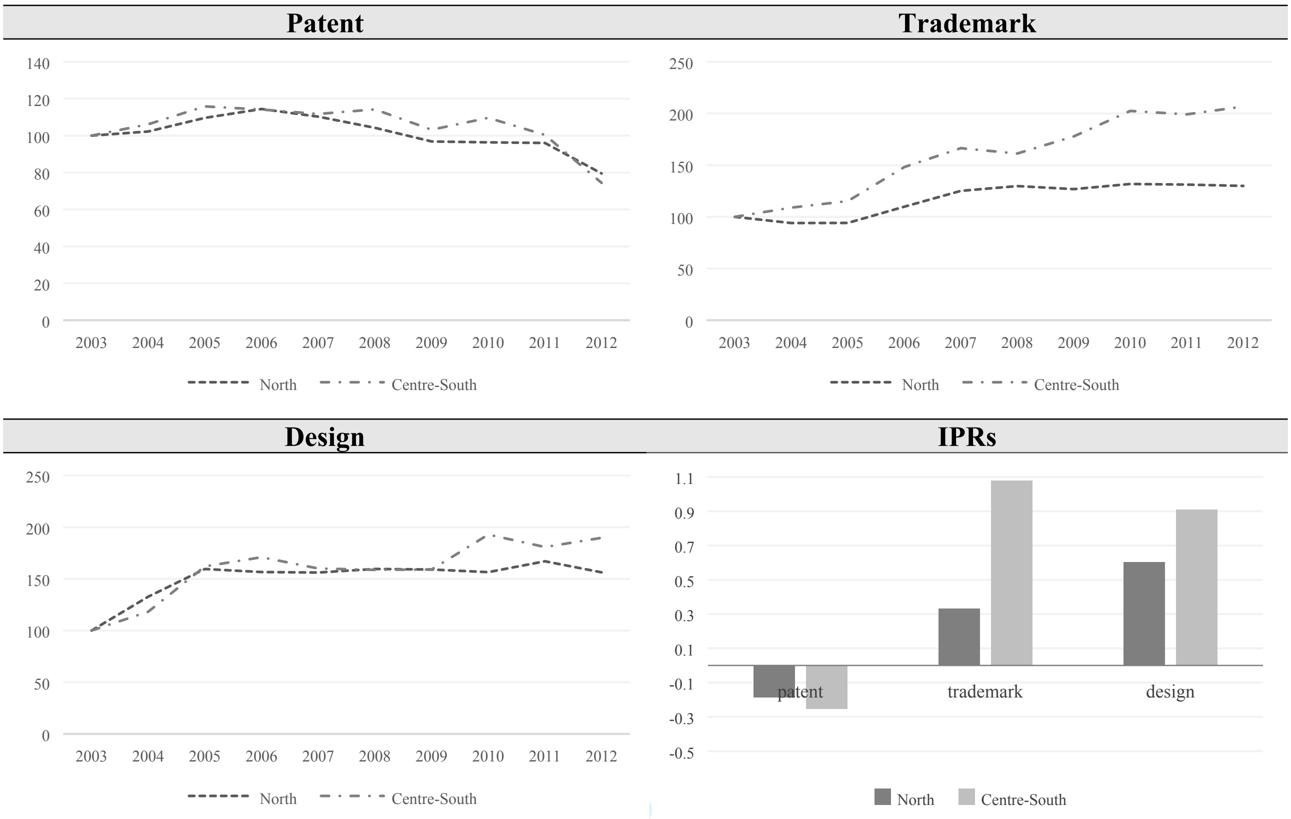
# Appendices

Appendix A.1. Top-10 provinces with highest and lowest IPR applications

| **Highest innovation** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Province | | Patent | Province | | Trademark | Province | | Design |
| Pordenone | north | 0.333 | Milan | north | 0.396 | Venice | north | 0.356 |
| Bologna | north | 0.272 | Parma | north | 0.320 | Treviso | north | 0.122 |
| Modena | north | 0.204 | Verona | north | 0.271 | Pordenone | north | 0.117 |
| Parma | north | 0.192 | Treviso | north | 0.252 | Udine | north | 0.107 |
| Vicenza | north | 0.187 | Vicenza | north | 0.249 | Vicenza | north | 0.090 |
| Treviso | north | 0.175 | Bologna | north | 0.245 | Verbano-Cusio-Ossola | north | 0.079 |
| Varese | north | 0.174 | Modena | north | 0.220 | Macerata | center | 0.077 |
| Milan | north | 0.170 | Florence | center | 0.209 | Modena | north | 0.065 |
| Reggio nell'Emilia | north | 0.167 | Bolzano | north | 0.188 | Milan | north | 0.065 |
| Turin | north | 0.165 | Siena | center | 0.187 | Bolzano | north | 0.064 |
| **Lowest innovation** | | | | | | | | |
| Province | | Patent | Province | | Trademark | Province | | Design |
| Crotone | south | 0.001 | Enna | south | 0.001 | Agrigento | south | 0.000 |
| Trapani | south | 0.004 | Crotone | south | 0.002 | Syracuse | south | 0.000 |
| Campobasso | south | 0.004 | Cosenza | south | 0.006 | Crotone | south | 0.001 |
| Agrigento | south | 0.004 | Reggio Calabria | south | 0.006 | Caltanissetta | south | 0.001 |
| Vibo Valentia | south | 0.005 | Foggia | south | 0.009 | Foggia | south | 0.001 |
| Ragusa | south | 0.006 | Nuoro | south | 0.009 | Enna | south | 0.001 |
| Reggio Calabria | south | 0.006 | Messina | south | 0.009 | Cosenza | south | 0.001 |
| Enna | south | 0.006 | Oristano | south | 0.010 | Cagliari | south | 0.001 |
| Nuoro | south | 0.007 | Syracuse | south | 0.010 | Rieti | center | 0.001 |
| Palermo | south | 0.007 | Caltanissetta | south | 0.011 | Palermo | south | 0.001 |

*Notes*: Averages over the period 2003–2012. Patent, trademark and design applications per 1000 inhabitants. Authors elaboration with data retrieved from Eurostat Regional Database.

Appendix A.2. Intellectual propriety rights applications by Italian macro-areas




*Notes*: IPRs by Italian macro-regions from 2003–2012, where 2003 = 100. (a) patent applications per 1000 inhabitants; (b) trademark applications per 1000 inhabitants; (c) design applications per 1000 inhabitants; (d) growth in 2003–2012 of IPRs per 1000 inhabitants.

Appendix A.3. Weight of international and internal migration by skill level

| | International (%) | | | Internal (%) | | |
|---|---|---|---|---|---|---|
| | 2003 | 2012 | 2003-2012* | 2003 | 2012 | 2003-2012* |
| *Low-skilled* | 60 | 53 | 60 | 56 | 51 | 53 |
| *Medium-high skilled* | 40 | 47 | 40 | 44 | 49 | 47 |

*Notes*: *Averages over the period 2003–2012. Authors elaboration with ISTAT data not publicly available.

Appendix A.4. Top 10 province destination of international and internal migration by skill level

| Medium-High-skilled | | | | | | Low-skilled | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| International | | | Internal | | | International | | | Internal | | |
| Agrigento | south | 0.639 | Bologna | north | 7.186 | Agrigento | south | 1.499 | Lodi | north | 8.666 |
| Pesaro and Urbino | center | 0.554 | Viterbo | center | 6.386 | Enna | south | 1.144 | Pavia | north | 8.476 |
| Milan | north | 0.472 | Rieti | center | 6.272 | Crotone | south | 1.102 | Vercelli | north | 8.104 |
| Imperia | north | 0.431 | Milan | north | 6.251 | Cosenza | south | 1.011 | Asti | north | 7.469 |
| Trieste | north | 0.430 | Lodi | north | 5.985 | Lecce | south | 0.895 | Rieti | center | 7.350 |
| Cosenza | south | 0.417 | Pisa | center | 5.917 | Vibo Valentia | south | 0.883 | Novara | north | 7.253 |
| Genoa | north | 0.391 | Siena | center | 5.911 | Isernia | south | 0.735 | Caserta | south | 7.077 |
| Ascoli Piceno | center | 0.355 | Pavia | north | 5.892 | Caltanissetta | south | 0.711 | Reggio nell'Emilia | center | 6.991 |
| Belluno | north | 0.343 | La Spezia | north | 5.877 | Pesaro and Urbino | center | 0.701 | Viterbo | north | 6.987 |
| Enna | south | 0.639 | Parma | north | 5.756 | Imperia | north | 0.674 | Pistoia | center | 6.790 |

*Notes*: Averages over the period 2003–2012. Medium- to high-skilled and low-skilled international and internal per 1000 inhabitants. Authors elaboration with ISTAT data not publicly available.

Appendix A.5. Pairwise correlation matrix

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) | (17) | (18) | (19) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) ln_patent | 1 | | | | | | | | | | | | | | | | | | |
| (2) ln_trademark | 0.767 | 1 | | | | | | | | | | | | | | | | | |
| (3) ln_design | 0.726 | 0.740 | 1 | | | | | | | | | | | | | | | | |
| (4) $mig^{inter\_medhigh}$ | -0.069 | -0.056 | -0.055 | 1 | | | | | | | | | | | | | | | |
| (5) $mig^{low}$ | -0.445 | -0.448 | -0.396 | 0.688 | 1 | | | | | | | | | | | | | | |
| (6) $mig^{intra\_medhigh}$ | 0.438 | 0.357 | 0.345 | -0.009 | -0.338 | 1 | | | | | | | | | | | | | |
| (7) $mig^{intra\_low}$ | 0.254 | 0.111 | 0.108 | -0.078 | -0.163 | 0.718 | 1 | | | | | | | | | | | | |
| (8) rd | 0.092 | 0.133 | 0.157 | 0.092 | -0.001 | 0.061 | -0.103 | 1 | | | | | | | | | | | |
| (9) graduates | 0.111 | 0.149 | 0.129 | 0.150 | -0.003 | 0.028 | -0.159 | 0.150 | 1 | | | | | | | | | | |
| (10) ln_pop | 0.216 | 0.246 | 0.160 | -0.009 | -0.130 | -0.234 | -0.366 | -0.194 | 0.170 | 1 | | | | | | | | | |
| (11) open | 0.433 | 0.381 | 0.325 | -0.079 | -0.276 | 0.220 | 0.182 | -0.069 | -0.042 | 0.068 | 1 | | | | | | | | |
| (12) i-district | 0.554 | 0.544 | 0.553 | -0.105 | -0.268 | 0.234 | 0.243 | -0.141 | 0.059 | 0.024 | 0.340 | 1 | | | | | | | |
| (13) sectoral | 0.602 | 0.524 | 0.605 | -0.099 | -0.249 | 0.169 | 0.224 | -0.011 | -0.033 | -0.016 | 0.432 | 0.769 | 1 | | | | | | |
| (14) sme-size | -0.075 | 0.079 | 0.095 | -0.253 | -0.195 | -0.076 | -0.063 | -0.004 | -0.088 | -0.194 | 0.080 | 0.266 | 0.250 | 1 | | | | | |
| (15) large-size | 0.614 | 0.563 | 0.528 | 0.019 | -0.307 | 0.193 | -0.015 | 0.101 | 0.097 | 0.277 | 0.429 | 0.253 | 0.462 | -0.025 | 1 | | | | |
| (16) med-high-tech | 0.673 | 0.488 | 0.518 | 0.003 | -0.266 | 0.313 | 0.252 | 0.019 | 0.039 | 0.166 | 0.418 | 0.389 | 0.618 | -0.110 | 0.702 | 1 | | | |
| (17) med-low-tech | 0.409 | 0.269 | 0.391 | -0.058 | -0.162 | 0.105 | 0.129 | -0.018 | -0.087 | -0.020 | 0.391 | 0.436 | 0.597 | 0.162 | 0.332 | 0.572 | 1 | | |
| (18) low-tech | 0.287 | 0.321 | 0.353 | -0.012 | -0.046 | 0.031 | 0.132 | -0.043 | 0.034 | -0.107 | 0.173 | 0.649 | 0.696 | 0.194 | 0.125 | 0.120 | 0.065 | 1 | |
| (19) kis | 0.017 | -0.005 | -0.106 | 0.147 | 0.008 | 0.140 | -0.022 | 0.005 | 0.256 | 0.324 | -0.109 | -0.284 | -0.420 | -0.674 | -0.028 | -0.030 | -0.310 | -0.357 | 1 |

*Notes*: The mean VIF of equation in Table 2 columns (1-3a) is 2.37; (1-3b) 2.42; (1-3c) 2.56.

## Appendix A.6. Estimations on patents, trademarks and designs: OLS results

| | Patent | | | Trademark | | | Design | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1a) | (1b) | (1c) | (2a) | (2b) | (2c) | (3a) | (3b) | (3c) |
| $mig^{inter\_medhigh}$ | -0.328 | -0.310 | -0.358 | 0.748** | 0.881** | 0.656* | -0.693* | -0.567 | -0.684* |
| | [0.262] | [0.270] | [0.281] | [0.343] | [0.355] | [0.340] | [0.365] | [0.351] | [0.368] |
| $mig^{inter\_low}$ | 0.018 | 0.017 | 0.036 | -0.262 | -0.301 | -0.255 | 0.252 | 0.272 | 0.259 |
| | [0.155] | [0.156] | [0.158] | [0.204] | [0.205] | [0.209] | [0.181] | [0.180] | [0.184] |
| $mig^{intra\_medhigh}$ | 0.097*** | 0.075*** | 0.082*** | 0.112*** | 0.112*** | 0.102*** | 0.291*** | 0.269*** | 0.298*** |
| | [0.026] | [0.026] | [0.027] | [0.035] | [0.035] | [0.035] | [0.037] | [0.036] | [0.037] |
| $mig^{intra\_low}$ | -0.033* | -0.015 | -0.033* | -0.041 | -0.033 | -0.032 | -0.116*** | -0.103*** | -0.082*** |
| | [0.018] | [0.018] | [0.018] | [0.026] | [0.026] | [0.026] | [0.028] | [0.028] | [0.028] |
| rd | 0.341*** | 0.394*** | 0.361*** | 0.311*** | 0.309*** | 0.336*** | 0.115 | 0.179* | 0.152 |
| | [0.088] | [0.096] | [0.093] | [0.085] | [0.079] | [0.083] | [0.119] | [0.106] | [0.118] |
| graduates $_{2002}$ | 0.431*** | 0.310*** | 0.326*** | 0.148 | 0.116 | 0.167 | -0.107 | -0.193 | -0.056 |
| | [0.076] | [0.079] | [0.072] | [0.106] | [0.102] | [0.105] | [0.127] | [0.128] | [0.130] |
| ln_pop $_{2002}$ | 0.455*** | 0.430*** | 0.424*** | 0.564*** | 0.563*** | 0.573*** | 0.532*** | 0.585*** | 0.686*** |
| | [0.032] | [0.037] | [0.037] | [0.047] | [0.051] | [0.051] | [0.051] | [0.054] | [0.057] |
| open | 0.002** | 0.002** | 0.002** | 0.000 | 0.000 | 0.001 | -0.003*** | -0.002*** | -0.003*** |
| | [0.001] | [0.001] | [0.001] | [0.001] | [0.001] | [0.001] | [0.001] | [0.001] | [0.001] |
| i-district | -0.149** | 0.204*** | 0.056 | 0.555*** | 0.624*** | 0.407*** | 0.481*** | 0.756*** | 0.435*** |
| | [0.068] | [0.062] | [0.071] | [0.092] | [0.086] | [0.094] | [0.124] | [0.121] | [0.135] |
| *share of employment* | | | | | | | | | |
| sectoral | 0.016*** | | | 0.007*** | | | 0.019*** | | |
| | [0.002] | | | [0.003] | | | [0.003] | | |
| sme-size | | 0.006** | | | 0.011*** | | | 0.018*** | |
| | | [0.003] | | | [0.003] | | | [0.004] | |
| large-size | | 0.026*** | | | 0.024*** | | | 0.013 | |
| | | [0.005] | | | [0.007] | | | [0.009] | |
| med-high-tech | | | 0.040*** | | | -0.006 | | | -0.034*** |
| | | | [0.006] | | | [0.008] | | | [0.010] |
| med-low-tech | | | 0.009 | | | 0.001 | | | 0.070*** |
| | | | [0.008] | | | [0.010] | | | [0.011] |
| low-tech | | | 0.014*** | | | 0.027*** | | | 0.022*** |
| | | | [0.004] | | | [0.006] | | | [0.007] |
| kis service | | | -0.001 | | | 0.007 | | | -0.013* |
| | | | [0.005] | | | [0.007] | | | [0.008] |
| costant | -9.087*** | -8.890*** | -8.710*** | -10.860*** | -11.398*** | -11.038*** | -12.281*** | -13.393*** | -14.301*** |
| | [0.463] | [0.550] | [0.518] | [0.679] | [0.748] | [0.736] | [0.766] | [0.824] | [0.813] |
| Observations | 1,030 | 1,030 | 1,030 | 1,030 | 1,030 | 1,030 | 1,030 | 1,030 | 1,030 |
| R-squared | 0.853 | 0.85 | 0.853 | 0.736 | 0.740 | 0.741 | 0.715 | 0.713 | 0.722 |
| Endog. test *p*-value | 0.001 | 0.001 | 0.001 | 0.046 | 0.039 | 0.036 | 0.562 | 0.942 | 0.985 |

*Notes*: The dependent variables are the log of *patent, trademark* and *design* applications per 1000 inhabitants at the province level (NUTS-3) for Italy, 2003–2012. See Table 1 for variable definitions. All models include year and region NUTS2 fixed effects. Standard errors are in bracket and robust to heteroskedasticity. Statistically significant a: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The omitted categories (high-tech and LKIS) are considered the most innovative and the least innovative sectors, respectively.

## Appendix A.7. First-stage test statistics

| | (1-3a) | (1-3b) | (1-3c) |
|---|---|---|---|
| ***F-test*** | | | |
| $mig^{inter\_medhigh}$ | 62.51 | 59.49 | 57.68 |
| $mig^{inter\_low}$ | 75.67 | 78.82 | 75.00 |
| $mig^{inter\_low}$ | 378.29 | 364.55 | 331.53 |
| $mig^{intra\_low}$ | 743.26 | 685.15 | 654.07 |
| Cragg-Donald **Wald F statistic** | 46.93 | 41.98 | 39.59 |
| *Kleibergen-Paap* **Wald rk F** | 25.56 | 25.33 | 25.38 |
| **Stock and Yogo** critical values: | | | |
| 5% max. IV relative bias | | 16.85 | |
| 10% maximal IV size | | 16.38 | |
| 15% maximal IV size | | 8.96 | |
| 20% maximal IV size | | 6.66 | |
| 25% maximal IV size | | 5.53 | |

*Notes*: The table reports the first stage F-test, the weak identification robust test Kleibergen and Paap rk Wald F statistic, and the Stock and Yogo critical values of the estimations displayed in Table 2. The p-value in all F-tests is 0.000.



## Appendix A.8. Robustness check: Hansen J statistics

In our IV model, we cannot directly test the validity of the overidentification restrictions (Hansen J test) because the equations are exactly identified (L-K equal to zero). To provide a formal test of over-identification (i.e., whether the instruments are uncorrelated with the error terms), we follow the approach Orefice (2010) used in a study to test the relation of migration flows with per capita GDP in OECD destination countries. Orefice (2010) proposes to add surely orthogonal instruments "even if irrelevant" as a way to test the exogeneity of the actual instruments. In our case, the instruments are those listed in equations 2 and 3.

The approach consists of first estimating a restricted model with only the surely orthogonal instruments and an unrestricted model with all the instruments. For the restricted model, we use surely orthogonal instruments: the number of deaths for suicide per 100000 inhabitants (used also in Orefice 2010), the ratio of childcare services over child population, the efficiency of water distribution for human consumption, the number of robberies over income, and the population density of 1921 of the destination province with all variables coming from the national statistical office of ISTAT.

As a second step, the Hansen J's statistics are calculated. If these increases significantly when all instruments are included and the null hypothesis is rejected, then the validity of the instruments should be called into question. In our three unrestricted models, the null hypothesis of exogeneity of the core instruments could not be rejected, so we can conclude that our instruments are valid (see table below).

| | Patent | | | Trademark | | | Design | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1a) | (1b) | (1c) | (2a) | (2b) | (2c) | (3a) | (3b) | (3c) |
| **Hansen J statistics** | | | | | | | | | |
| Unrestricted model *surely orthogonal and core instruments* | 0.314 | 0.0782 | 0.177 | 0.050 | 0.101 | 0.217 | 0. 051 | 0.108 | 0.091 |

*Notes*: The table reports the ($p$-val) of the Hansen J statistics overidentification test of instruments for each model.

## Appendix A.9. Limited Information Maximum Likelihood (LIML) estimations on designs

| | **LIML** (a) | **LIML** (b) | **LIML** (c) |
|---|---|---|---|
| $mig^{inter\_medhigh}$ | -1.313 | -0.017 | -0.443 |
| | [0.922] | [0.936] | [1.005] |
| $mig^{inter\_low}$ | 0.485 | 0.1 | 0.225 |
| | [0.373] | [0.383] | [0.407] |
| $mig^{intra\_medhigh}$ | 0.342*** | 0.247*** | 0.299*** |
| | [0.058] | [0.058] | [0.056] |
| $mig^{intra\_low}$ | -0.158*** | -0.096** | -0.079** |
| | [0.040] | [0.040] | [0.038] |
| rd | 0.102 | 0.189* | 0.155 |
| | [0.120] | [0.105] | [0.119] |
| graduates $_{2002}$ | -0.101 | -0.204 | -0.067 |
| | [0.133] | [0.134] | [0.132] |
| ln_pop $_{2002}$ | 0.533*** | 0.570*** | 0.687*** |
| | [0.062] | [0.062] | [0.066] |
| open | -0.003*** | -0.002*** | -0.003*** |
| | [0.001] | [0.001] | [0.001] |
| i-district | 0.489*** | 0.750*** | 0.442*** |
| | [0.124] | [0.122] | [0.135] |
| *share of employment* | | | |
| sectoral | 0.019*** | | |
| | [0.003] | | |
| sme-size | | 0.019*** | |
| | | [0.004] | |
| large-size | | 0.013 | |
| | | [0.009] | |
| med-high-tech | | | -0.034*** |
| | | | [0.010] |
| med-low-tech | | | 0.071*** |
| | | | [0.011] |
| low-tech | | | 0.022*** |
| | | | [0.007] |
| kis service | | | -0.014* |
| | | | [0.008] |
| costant | -12.209*** | -13.255*** | -14.358*** |
| | [0.875] | [0.901] | [0.945] |
| Observations | 1,030 | 1,030 | 1,030 |
| R-squared | 0.714 | 0.712 | 0.722 |

*Notes*: See Table 1 for variable definitions. All models include year and region (NUTS2) fixed effects. Standard errors are in bracket and robust to heteroskedasticity. Statistically significant a: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

## Appendix A.10. Macro-territorial estimations of patents: 2SLS results

| | Nord | | | Center-South | | |
|---|---|---|---|---|---|---|
| | (1a) | (1b) | (1c) | (2a) | (2b) | (2c) |
| $mig^{inter\_medhigh}$ | -0.132 | 0.598 | 0.469 | -2.656* | -2.493 | -2.080* |
| | [0.511] | [0.666] | [0.716] | [1.595] | [1.617] | [1.458] |
| $mig^{inter\_low}$ | -0.489 | -0.949** | -0.645 | 0.763 | 0.645 | 0.542 |
| | [0.375] | [0.430] | [0.479] | [0.527] | [0.546] | [0.493] |
| $mig^{intra\_medhigh}$ | 0.141*** | 0.094*** | 0.137*** | 0.366*** | 0.322*** | 0.386*** |
| | [0.033] | [0.036] | [0.033] | [0.129] | [0.111] | [0.118] |
| $mig^{intra\_low}$ | -0.045* | 0.001 | -0.036 | -0.215*** | -0.210*** | -0.250*** |
| | [0.024] | [0.027] | [0.023] | [0.068] | [0.063] | [0.063] |
| rd | 0.188** | 0.323*** | 0.235*** | 0.360** | 0.344** | 0.352** |
| | [0.083] | [0.094] | [0.089] | [0.145] | [0.143] | [0.142] |
| graduates $_{2002}$ | 0.164** | -0.167* | 0.003 | 0.664*** | 0.738*** | 0.653*** |
| | [0.079] | [0.089] | [0.072] | [0.153] | [0.143] | [0.139] |
| ln_pop $_{2002}$ | 0.408*** | 0.361*** | 0.358*** | 0.495*** | 0.393*** | 0.464*** |
| | [0.037] | [0.042] | [0.039] | [0.075] | [0.087] | [0.098] |
| open | 0.001 | 0.002 | 0.002* | 0.002*** | 0.001 | 0.002* |
| | [0.001] | [0.001] | [0.001] | [0.001] | [0.001] | [0.001] |
| i-district | -0.222*** | 0.238*** | -0.060 | 0.214 | 0.434*** | 0.562*** |
| | [0.071] | [0.064] | [0.078] | [0.145] | [0.131] | [0.173] |
| *share of employment* | | | | | | |
| sectoral | 0.022*** | | | 0.007 | | |
| | [0.002] | | | [0.005] | | |
| sme-size | | 0.015*** | | | 0.000 | |
| | | [0.004] | | | [0.004] | |
| large-size | | 0.037*** | | | 0.035*** | |
| | | [0.005] | | | [0.014] | |
| med-high-tech | | | 0.050*** | | | 0.039*** |
| | | | [0.006] | | | [0.011] |
| med-low-tech | | | 0.019** | | | -0.002 |
| | | | [0.008] | | | [0.019] |
| low-tech | | | 0.030*** | | | -0.007 |
| | | | [0.005] | | | [0.008] |
| kis service | | | -0.016* | | | -0.011 |
| | | | [0.008] | | | [0.009] |
| costant | -8.621*** | -8.596*** | -8.062*** | -11.537*** | -10.055*** | -10.700*** |
| | [0.568] | [0.700] | [0.661] | [1.080] | [1.233] | [1.356] |
| Observations | 460 | 460 | 460 | 570 | 570 | 570 |
| R-squared | 0.704 | 0.677 | 0.719 | 0.726 | 0.733 | 0.738 |
| Endog. test [a] | | | | | | |
| (p-value) | 0.005 | 0.010 | 0.006 | 0.081 | 0.050 | 0.017 |

*Notes*: The table report the full model of Table 3. The dependent variables are the logarithm of *patent* applications per 1000 inhabitants at the province (NUTS-3) level for Italy, 2003-2012. See Table 1 for variable definitions. All models include year and region NUTS2 fixed effects. Standard errors are in bracket and robust to heteroskedasticity. Statistically significant a: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

[a] The F-test of the first-stage are reported in Appendix A.13.

## Appendix A.11. 2SLS regressions of the macro-territorial estimations of trademarks

| | Nord | | | Center-South | | |
|---|---|---|---|---|---|---|
| | (1a) | (1b) | (1c) | (2a) | (2b) | (2c) |
| $mig^{inter\_medhigh}$ | 1.324* | 2.061** | 1.427 | -3.903* | -1.159 | -3.695* |
| | [0.751] | [1.049] | [1.111] | [2.327] | [2.303] | [2.116] |
| $mig^{inter\_low}$ | 0.389 | -0.096 | 0.294 | 1.300 | 0.414 | 1.210 |
| | [0.540] | [0.627] | [0.765] | [0.791] | [0.795] | [0.737] |
| $mig^{intra\_medhigh}$ | 0.086* | 0.088 | 0.107** | 0.687*** | 0.485*** | 0.658*** |
| | [0.052] | [0.054] | [0.050] | [0.164] | [0.145] | [0.166] |
| $mig^{intra\_low}$ | 0.013 | 0.036 | 0.027 | -0.361*** | -0.268*** | -0.316*** |
| | [0.039] | [0.041] | [0.037] | [0.097] | [0.086] | [0.093] |
| rd | 0.020 | -0.009 | 0.037 | 0.603*** | 0.616*** | 0.610*** |
| | [0.078] | [0.075] | [0.080] | [0.108] | [0.110] | [0.106] |
| graduates $_{2002}$ | 0.084 | 0.007 | 0.251* | -0.048 | -0.024 | 0.000 |
| | [0.152] | [0.142] | [0.144] | [0.212] | [0.176] | [0.199] |
| ln_pop $_{2002}$ | 0.505*** | 0.469*** | 0.598*** | 0.812*** | 0.749*** | 0.942*** |
| | [0.056] | [0.059] | [0.059] | [0.108] | [0.129] | [0.142] |
| open | 0.006** | 0.003 | 0.005** | 0.000 | -0.001 | -0.002 |
| | [0.002] | [0.002] | [0.002] | [0.001] | [0.001] | [0.001] |
| i-district | 0.553*** | 0.599*** | 0.418*** | 0.650*** | 0.923*** | 0.680*** |
| | [0.112] | [0.100] | [0.108] | [0.180] | [0.152] | [0.228] |
| *share of employment* | | | | | | |
| sectoral | 0.004 | | | 0.023*** | | |
| | [0.003] | | | [0.006] | | |
| sme-size | | 0.011* | | | 0.018*** | |
| | | [0.006] | | | [0.005] | |
| large-size | | 0.026*** | | | 0.032* | |
| | | [0.008] | | | [0.019] | |
| med-high-tech | | | -0.015* | | | 0.006 |
| | | | [0.009] | | | [0.015] |
| med-low-tech | | | -0.008 | | | 0.094*** |
| | | | [0.012] | | | [0.026] |
| low-tech | | | 0.028*** | | | 0.032*** |
| | | | [0.007] | | | [0.010] |
| kis service | | | -0.012 | | | 0.001 |
| | | | [0.014] | | | [0.013] |
| costant | -10.735*** | -10.935*** | -11.716*** | -15.829*** | -15.605*** | -18.150*** |
| | [0.856] | [0.922] | [1.103] | [1.550] | [1.825] | [1.951] |
| Observations | 460 | 460 | 460 | 570 | 570 | 570 |
| R-squared | 0.564 | 0.565 | 0.599 | 0.598 | 0.66 | 0.612 |
| Endog. test [a] | | | | | | |
| (p-value) | 0.022 | 0.007 | 0.001 | 0.072 | 0.583 | 0.108 |

*Notes*: The table report the full model of Table 3. The dependent variables are the logarithm of *trademark* applications per 1000 inhabitants at the province (NUTS-3) level for Italy, 2003-2012. See Table 1 for variable definitions. All models include year and region NUTS2 fixed effects. Standard errors are in bracket and robust to heteroskedasticity. Statistically significant a: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

[a] For these estimates in the Centre-South tests failed to reject endogeneity. We implement LIML estimations. The 2SLS results are robust to using a LIML. The F-test of the first-stage are reported in Appendix A.13.

## Appendix A.12. 2SLS regressions of the macro-territorial estimations of designs

| | Nord | | | Center-South | | |
|---|---|---|---|---|---|---|
| | (1a) | (1b) | (1c) | (2a) | (2b) | (2c) |
| $mig^{inter\_medhigh}$ | -6.296*** | -4.753*** | -5.639*** | -2.470 | -0.121 | -3.639 |
| | [1.332] | [1.639] | [1.726] | [2.115] | [2.197] | [2.013] |
| $mig^{inter\_low}$ | 5.168*** | 4.582*** | 4.946*** | 0.514 | -0.283 | 0.876 |
| | [0.939] | [1.075] | [1.189] | [0.716] | [0.768] | [0.702] |
| $mig^{intra\_medhigh}$ | 0.560*** | 0.463*** | 0.522*** | 0.272* | 0.004 | 0.204 |
| | [0.072] | [0.076] | [0.068] | [0.149] | [0.142] | [0.142] |
| $mig^{intra\_low}$ | -0.173*** | -0.142** | -0.123** | -0.213*** | -0.102 | -0.118 |
| | [0.052] | [0.057] | [0.050] | [0.082] | [0.080] | [0.079] |
| rd | -0.341*** | -0.206* | -0.257** | 0.459*** | 0.464*** | 0.462*** |
| | [0.113] | [0.108] | [0.117] | [0.122] | [0.125] | [0.125] |
| graduates $_{2002}$ | 0.461** | 0.427* | 0.418* | -0.238 | -0.120 | -0.174 |
| | [0.233] | [0.237] | [0.225] | [0.196] | [0.191] | [0.198] |
| Population $_{2002}$ | 0.875*** | 0.906*** | 0.968*** | 0.455*** | 0.297** | 0.654*** |
| | [0.097] | [0.097] | [0.099] | [0.100] | [0.120] | [0.131] |
| open | 0.002 | 0.005* | 0.007** | -0.004*** | -0.004*** | -0.006*** |
| | [0.003] | [0.003] | [0.003] | [0.001] | [0.001] | [0.001] |
| i-district | 0.236 | 0.360** | 0.205 | 0.454** | 1.062*** | 0.210 |
| | [0.185] | [0.176] | [0.192] | [0.195] | [0.179] | [0.242] |
| *share of employment* | | | | | | |
| sectoral | 0.014*** | | | 0.033*** | | |
| | [0.004] | | | [0.006] | | |
| sme-size | | 0.017* | | | 0.013*** | |
| | | [0.009] | | | [0.005] | |
| large-size | | -0.013 | | | 0.049*** | |
| | | [0.012] | | | [0.018] | |
| med-high-tech | | | -0.056*** | | | -0.017 |
| | | | [0.014] | | | [0.015] |
| med-low-tech | | | 0.076*** | | | 0.157*** |
| | | | [0.015] | | | [0.024] |
| low-tech | | | 0.000 | | | 0.064*** |
| | | | [0.008] | | | [0.011] |
| kis service | | | -0.006 | | | 0.026** |
| | | | [0.019] | | | [0.011] |
| costant | -17.806*** | -18.601*** | -19.220*** | -12.271*** | -10.318*** | -16.540*** |
| | [1.421] | [1.416] | [1.718] | [1.447] | [1.723] | [1.821] |
| Observations | 460 | 460 | 460 | 570 | 570 | 570 |
| R-squared | 0.468 | 0.488 | 0.518 | 0.649 | 0.647 | 0.651 |
| Endog. test [a] | | | | | | |
| (*p*-value) | 0.000 | 0.008 | 0.004 | 0.167 | 0.146 | 0.244 |

*Notes*: The table reports the full model of Table 3. The dependent variables are the logarithm of *design* applications per 1000 inhabitants at the province (NUTS-3) level for Italy, 2003–2012. See Table 1 for variable definitions. All models include year and region NUTS2 fixed effects. Standard errors are in bracket and robust to heteroskedasticity. Statistically significant a: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
[a] The endogeneity test fails to reject exogeneity for the Centre-South. We implement LIML estimations. The 2SLS results are robust to using a LIML. The F-tests of the first-stage are reported in Appendix A.13.

## Appendix A.13. First-stage test statistics of the macro-territorial estimations

| | Nord | | | Center-South | | |
|---|---|---|---|---|---|---|
| | (1a) | (1b) | (1c) | (2a) | (2b) | (2c) |
| $mig^{inter\_medhigh}$ | 91.28 | 77.76 | 58.59 | 47.53 | 56.61 | 65.32 |
| $mig^{inter\_low}$ | 26.00 | 21.34 | 25.28 | 115.84 | 121.79 | 125.01 |
| $mig^{inter\_low}$ | 364.67 | 469.41 | 374.93 | 71.98 | 70.09 | 57.64 |
| $mig^{intra\_low}$ | 634.55 | 624.88 | 691.58 | 140.53 | 132.52 | 123.82 |

*Notes*: The table reports the F-test of the first-stage of the macro-territorial estimations displayed in Appendix A10-12. The p-value in all F-test is 0.000.

# References

Orefice, Gianluca. 2010. “Skilled Migration and Economic Performances: Evidence from OECD Countries.” *Swiss Journal of Economics and Statistics* 146 (4). doi:10.1007/BF03399337.

Dear Editor,

we wish to thank you for giving us the opportunity to address the remaining concerns.

As you will see, the paper has now been carefully edited (from abstract to conclusions), shortening what was unnecessary, while adding sentences to clarify what was not clear and explain what was newly added. Below we detail all the changes to address the specific concerns of the referees, but we start by responding to your own summary of the remaining concerns.

Overall, we feel that the manuscript has greatly improved at this round.

We look forward to hearing back from you,

The authors



*The Reviewers and I see improvements in your work and would like to commend you for your effort in addressing the suggestions and recommendations received in the previous round. However, there are still some minor concerns, which despite being easy to fix are crucial to address in order to move the paper closer to publication.*

*Let me reiterate what these concerns are and add a few final suggestions of my own. I advise you to address each of them convincingly.*

*1. The reviewers still raise concerns about the validity of the instruments, especially of those used for intra-national mobility. This is important, especially because your main contribution stems from those analyses and from the different effects your find for international and intranational mobility. We are aware that there is no easy way to test the validity of the instruments, so I strongly recommend you toning down causality claims throughout the paper, clarify that you can at best claim associations between migration and innovation, acknowledge the limitations of your empirical approach, add a few more thoughts that could convince the reader about the potential validity of your instruments while encouraging future research to keep improving your approach.*

<u>Answer:</u> We understand the concern and have followed the suggestions. First, we clarified the limitations of our IV in section 3.4. Second, we followed the advice given by reviewer 1 (point 3) and introduced a set of standard tests to check the relevance and validity of the instruments (section 3.4, pages 16). Third, we mentioned in the conclusions that further improvements can be implemented in future research (section 5, page 23). Overall, we have taken care of using correlational language only. This is why we also changed the title, from focusing effects to focusing on relationships.

*2. There are also concerns regarding the value of including lagged values of your DVs versus the initial values of those DVs in the set of explanatory/control variables, so it is important that you reconsider this choice and show that your results are consistent when you do not include those lags (or initial values). Related to this, there is a general confusion regarding at which level you include fixed effects in your regression – NUTS2 or NUTS3? Your level of analysis is NUTs3 but in footnotes you describe that FE are at NUTs2 – why? Wouldn't it make more sense to include FE at the same level of the unit of analysis (NUTs3)? In this latter case, any time-invariant variables will be absorbed by the fixed effect.*

Answer: We agree with the concern that the inclusion of the lagged DVs among the regressors may increase endogeneity. To mitigate this potential problem, we follow the advice of reviewer 1 (point 2) and remove them. Their inclusion in fact must be done with a sufficient time lag (as reviewer 3 indicates in point 3), but this is not possible in our case since data on designs are only available since 2003, and, for consistency, the equations must be the same for all IPRs.

To improve the robustness of our results, we also followed the advice of reviewer 3 (point 3) and did a check on patents by including among the regressors the 1995 log number of patent applications per 1000inhabitants, and for trademarks the 1996 (first year available). The results confirm those obtained in the new models (without the DV among regressors). The results of this robustness check have been annexed at the end of this document.

As for NUTS2 fixed effects, we had to opt for these, instead of using NUTS3 fixed effects, since we have a short time interval and migration flows in the provinces are quite persistent. This problem was also emphasized by Niebuhr (2010). The use of NUTS2 effects aligns with approaches taken by others in similar studies (see Bratti and Conti 2018; Bratti, De Benedictis, and Santoni 2014; Wagner, Head, and Ries 2002). This approach enables capturing temporal and cross-sectional variation between regions. Bratti and Conti (2018) considered this intermediate approach to be particularly effective for a country like Italy. We have explained our choice in footnote [4].

*3. You do not provide much elaboration on the size of the coefficients, and it would be important to comment on the direction of the bias that you may be correcting with your IV estimation. Oftentimes the IV-coefficients become larger in size, and this may reveal something about the direction of the bias (positive/negative). It would be important to understand a bit better what the IV-models are indeed trying to correct (e.g. provide some elaboration on what are the key unobservables that may be playing a role here, how they correlate with both migration flows and innovation, and why this may be inflating or underestimating the coefficients of interest in a simpler, OLS model).*

Answer: We thank the referee for this important suggestion. To improve the explanation of the results we have followed your advice and included an additional discussion on the direction of the bias we are trying to correct with our IV and what possible key unobservable variable may be playing a role (see Section 4.1, page 19).

*4. I also strongly recommend adding some elaboration on effect sizes – e.g. if migration of different kinds increases by 1-standard deviation, how much are patents, trademarks and designs expected to vary? I see that you take the log of your DV (though I am unsure whether the statistics provided in table 1 are before or after taking the log); this may change interpretation of coefficients, so it is crucial to provide some examples to guide the reader. By the way, are the results consistent when the DV is not measured in log, but simply reflect the innovation output per 1,000 inhabitants?*

Answer: We thank the referee for this advice. We have included the estimated effect-sizes in a new summary table (as you suggest doing in the next point) and we better explain how to interpret coefficients (see page 21).

*I see that you take the log of your DV (though I am unsure whether the statistics provided in table 1 are before or after taking the log)*

We have updated table [1] of the descriptive analysis and now display the statistics of the log IPR filings.

On the log of DV, this is quite common in the literature since innovation tends to have a skewed distribution. This is especially the case in Italy where strong economic differences between regions are persistent over time and, as Figure 2 shows, most provinces in the Centre-South have low levels of performance, as opposed to the North. Therefore, in order to make the dependent variables normally distributed and the results comparable with previous research, we use the log.

*5. One reviewer also suggests adding a summary table – I agree this could add value. Please consider adding a simple table, where for example you could have the three innovation outcomes in columns and the types of migration in rows. Each cell could then have a brief summary of the main result found (non-significant association, positive association, negative association, also possibly different by north/south if applicable). You could also add a note about where in the paper those results can be found – e.g. by referring to the table* *where the results are reported. If there is space, you could consider adding the effect size in that table – using the most final model as a reference.*

Answer: This sounds like a very useful addition. We added a summary table [4]. To respond to your previous point too, we decided to include the effect sizes in this table, together with the significance. In the text we briefly explain the contents of this table (section 4.3).

*6. While I am aware this may take space, I think you can save space by streamlining some tables – e.g. Tables 5-6-7 can be made shorter by omitting the control variables and reporting only the key coefficients of interest on migration. These three tables could be condensed in one – e.g. table 5a, 5b, 5c, where each "panel" refers to one different DV. A full version of the tables could then be reported in appendix. Likewise, there are opportunities to move some figures to the appendix – I suggest keeping all the maps in the main paper, together with figures 1a and 4a (maybe side-by-side, as these show the evolution of the two key types of variables – DV and Independent variables). The comparison between North/South could be shown with figure 3d. All the remaining figures could be moved to an appendix.*

Answer: We thank the referee for the suggestions: we have updated the tables and figures following them.

*7. Finally, before resubmitting, I would strongly recommend checking whether all the statistics and coefficients have the same number of decimals to make everything consistent. I also strongly recommend having the paper proofread by a professional editing service, as it may help make some paragraphs shorter and some sentences much clearer and more compelling.*

Answer: Having updated all the statistics, we did a double check to make sure we have the same number of decimals in the coefficients. We also had proofreading done by a professional editing service.

*Reviewer(s)' comments to author:*

***Reviewer: 1***

*Comments to the Author*
*I think the paper has benefitted substantially from this second round of revisions and I found it improved.*
*I still have some pending remarks:*

*1. I think that a summary table would help a lot summarising the main results. The impression I still have is that we are in front of many, rich results, but there are still problems in linking them one another. A synthesis table would help. The same applies to the analysis by macro regions, which is meant to be a robustness checks but provides instead a heterogeneous picture of IPR strategies across the country. While the comment developed by the author is correct, the interpretation is still underdeveloped.*

Answer: We thank the reviewer for highlighting this issue. We have followed the advice and included a table summarising the results (Table 4) with a brief explanation on how to interpret the coefficients (section 4.3). We also reorganized all the estimations results (tables and discussion).

*2. In terms of the econometric approach, I see some improvements and polishing but I think that the introduction of lagged variables worsens rather than mitigates endogeneity concerns. I would remove them.*

Answer: This point was also raised by the editor: we now remove the lagged dependent variable but discuss more at length the implications of this choice (see point 2 in the reply to the editor).

*3. Hansen test is not presented, so the reader is left with little information about the real necessity to move to 2SLS. If the latter turns to be warranted on the basis of the Hansen test, then the authors could focus on those estimates and keep the remaining in the appendix, so to slim the paper. Moreover, the strength of instruments* *is generally assessed on the basis of Cragg-Donald F statistic (and its robust analog, i.e., the Kleinberg-Paap rk Wald statistic) with respect to the tabulated Stock and Yogo (2005) critical values, being instruments weak the null hypothesis. I would recommend following this standard approach in assessing the need, validity and strength of instrument.*

Answer: We truly thank the reviewer for this advice. The Hansen test was not presented because the equation is exactly identified. However, to validate the instruments, we made a robustness check and relied on the approach used by Orefice (2010) that involves adding surely orthogonal instruments (detailed on page 16) to provide a overidentification test. We also added an endogeneity test under each regression (Table 2), to check the presence of endogeneity in the OLS model and, thus, whether to move to an IV panel model (2SLS).

As for relevance of our instruments, we follow the Reviewer's advice and included an F-test in the first-stage, the Cragg-Donald Wald F statistic, its robust analog Kleinberg-Paap rk and the critical values of Stock and Yogo (2005) (details are on page 16, and results of the tests in Appendix A.8).

***Reviewer: 2***

*Comments to the Author*
*Dear authors,*

*I'd like to congratulate you on your hard work on this paper. I have no further concerns.*

Answer: Many thanks for the positive evaluation of our paper.

***Reviewer: 3***

*Comments to the Author*

*The paper has certainly gone through a substantial improvement on many aspects, which have made it a very interesting read. Yet, some of the core points raised in the previous round were not really addressed, which leaves me with mixed feelings about the potential of this paper for publication.*

*1. In particular, the validity of the instrument for internal migration is actually still subject to the potential threats that I raised earlier – regardless of the presence of an origin-destination migration measure, the overall Italy-wide migration of skilled or unskilled workers may be driven by particular provinces (e.g. the opening of a multinational in a province). Stating that this is not the case as the authors do in their reply letter does not really help developing the argument. In the paper, the authors do not really argument about the validity of the instrument, but refer to a previous paper that employed it, Fratesi and Percoco. As a minimum, I would suggest that they cite some arguments about the instrument's validity from their paper.*

Answer: We agree on the need to better discuss our instruments. We clarified the limitations of our IV in section 3.4 and introduced a set of standard tests to check the relevance and validity of the instruments (section 3.4, pages 16). We also mentioned in the conclusions that improvements can be implemented also in future research (section 5, page 23).

*2. Moreover, while they report a number of tests that confirm the strength of the instrument (which was not in question), as they did not follow the suggestion to think of a different instrument, they cannot prove the exogeneity of the instrument itself. The endogeneity test that they report and to which they a bit confusingly refer to support their statements is not a way to test the validity of their instruments but a way to test the presence of endogeneity in the OLS model. I would recommend that the authors at least raise the potential concerns that one may have about this instrument and that they argument about why these concerns are unlikely to apply in their setting.*

Answer: We realize that at the previous round we did not explain that we tried different instruments (e.g., geological soil erosion). They were all weak and not correlated with the explanatory variables (very low R2 adjustment and F-test under 10). As we explained in the previous point, we better clarify the limitations and argument on the validity of our instruments by introducing a set of standard tests proposed by reviewer 1 (detailed in section 3.4). We also provide more details on the endogeneity tests that we ran (page 17).

*3. Another, related, econometric issue is the use of a lagged dependent variable among the first-stage regressors. In the previous round, I had asked clarification about the role of this variable and this has been removed from the main equation but is actually still in the results. The authors just state rather unconvincingly that they took it from Bratti and Conti, but Bratti and Conti include the number of patents at the beginning of the period (1995) and not one year before migration. Are the results robust to including start-of-period IPR measures? By the way, on page 16, I think the sentence "included in the regressions the logarithm of the number of IPRs applications per capita, fixed at a year predicting of the estimation period" should be replaced by "included in the regressions the logarithm of the number of IPRs applications per capita, fixed at a year predating the estimation period"*

Answer: We are sorry to hear that this point is still unclear. The editor also pointed at this issue, please see our response to point 2 in the response to the editor's comments.

*4. Finally, there needs to be a specification about the fixed effects included in the model, which I understand are NUTS2 level as in Bratti and Conti (2018), and Bratti et al (2014), but from the discussion and equation could be easily misled with NUTS3 fixed effects.*

Answer: We thank the reviewer for raising this point. In the methodology, we clarified the use of fixed effects at NUTS2 level (page 13) and added a footnote [4].

*Good luck!*

Thank you!

Table. 2SLS estimations with patents among the regressors fixed at 1995 (start-of-period).

| | Patent | | |
|---|---|---|---|
| | (a) | (b) | (c) |
| $mig^{inter\_medhigh}$ | -1.352** | -1.283** | -1.138* |
| | [0.606] | [0.643] | [0.654] |
| $mig^{inter\_low}$ | 0.368 | 0.344 | 0.274 |
| | [0.249] | [0.258] | [0.268] |
| $mig^{intra\_medhigh}$ | 0.130*** | 0.086** | 0.110*** |
| | [0.039] | [0.039] | [0.038] |
| $mig^{intra\_low}$ | -0.074*** | -0.043* | -0.067*** |
| | [0.024] | [0.024] | [0.024] |
| $ln\_patent_{1995}$ | 0.199*** | 0.222*** | 0.209*** |
| | [0.028] | [0.028] | [0.028] |
| rd | 0.269*** | 0.303*** | 0.279*** |
| | [0.080] | [0.085] | [0.082] |
| $graduates_{2002}$ | 0.465*** | 0.387*** | 0.411*** |
| | [0.071] | [0.074] | [0.068] |
| $ln\_pop_{2002}$ | 0.363*** | 0.334*** | 0.343*** |
| | [0.038] | [0.040] | [0.039] |
| open | 0.001* | 0.001* | 0.001* |
| | [0.001] | [0.001] | [0.001] |
| i-district | -0.070 | 0.186*** | 0.026 |
| | [0.067] | [0.061] | [0.067] |
| *share of employment* | | | |
| sectoral | 0.012*** | | |
| | [0.002] | | |
| sme-size | | 0.004 | |
| | | [0.003] | |
| large-size | | 0.019*** | |

| | | | |
|---|---|---|---|
| | | [0.005] | |
| med-high-tech | | | 0.026*** |
| | | | [0.006] |
| med-low-tech | | | 0.012* |
| | | | [0.008] |
| low-tech | | | 0.013*** |
| | | | [0.004] |
| kis service | | | -0.003 |
| | | | [0.005] |
| costant | -6.934*** | -6.519*** | -6.667*** |
| | [0.578] | [0.608] | [0.577] |
| Observations | 1,030 | 1,030 | 1,030 |
| R-squared | 0.859 | 0.858 | 0.861 |

*Notes*: The dependent variable is the logarithm of patent applications per 1000 inhabitants. The reported values correspond at NUTS3 level for Italy, 2003-2012. All models include year and region (NUTS2) fixed effects. Standard errors are in bracket and robust to heteroskedasticity. Statistically significant a: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table. 2SLS estimations with trademarks among the regressors fixed at 1996 (start-of-period).

| | **Trademark** | | |
|---|---|---|---|
| | (a) | (b) | (c) |
| $mig^{inter\_medhigh}$ | 0.130 | 0.917 | 0.132 |
| | [0.834] | [0.894] | [0.881] |
| $mig^{inter\_low}$ | -0.103 | -0.379 | -0.084 |
| | [0.349] | [0.363] | [0.368] |
| $mig^{intra\_medhigh}$ | 0.201*** | 0.202*** | 0.206*** |
| | [0.050] | [0.051] | [0.051] |
| $mig^{intra\_low}$ | -0.068** | -0.067* | -0.055 |
| | [0.034] | [0.035] | [0.035] |
| $ln\_trademark_{1996}$ | 0.292*** | 0.282*** | 0.287*** |
| | [0.023] | [0.024] | [0.024] |
| rd | 0.275*** | 0.253*** | 0.274*** |
| | [0.072] | [0.070] | [0.073] |
| $graduates_{2002}$ | 0.026 | 0.067 | 0.089 |
| | [0.099] | [0.098] | [0.099] |
| $ln\_pop_{2002}$ | 0.443*** | 0.467*** | 0.494*** |
| | [0.052] | [0.053] | [0.055] |
| open | 0.002* | 0.001 | 0.002** |
| | [0.001] | [0.001] | [0.001] |
| i-district | 0.703*** | 0.520*** | 0.536*** |
| | [0.079] | [0.080] | [0.084] |
| *share of employment* | | | |
| sectoral | -0.003 | | |
| | [0.002] | | |
| sme-size | | 0.011*** | |
| | | [0.004] | |
| large-size | | 0.003 | |
| | | [0.007] | |
| med-high-tech | | | -0.026*** |
| | | | [0.008] |
| med-low-tech | | | 0.010 |
| | | | [0.009] |
| low-tech | | | 0.005 |
| | | | [0.005] |
| kis service | | | 0.001 |
| | | | [0.007] |
| costant | -8.229*** | -9.183*** | -9.008*** |
| | [0.734] | [0.768] | [0.784] |
| Observations | 1,030 | 1,030 | 1,030 |

| | | | |
|---|---|---|---|
| R-squared | 0.771 | 0.774 | 0.773 |

*Notes*: The dependent variable is the logarithm of trademark applications per 1000 inhabitants. The reported values correspond at NUTS3 level for Italy, 2003-2012. All models include year and region (NUTS2) fixed effects. Standard errors are in bracket and robust to heteroskedasticity. Statistically significant a: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.