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Anna Maria Mayda, Gianluca Orefice, Gianluca Santoni

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Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
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Abstract

This paper analyses the impact of skilled migrants on the innovation (patenting) activity of French firms between 1995 and 2010, and investigates the underlying mechanism. We present district-level and firm-level estimates and address endogeneity using a modified version of the shift-share instrument. Skilled migrants increase the number of patents at both the district and firm level. Large, high-productivity and capital-intensive firms benefit the most, in terms of innovation activity, from skilled immigrant workers. Importantly, we provide evidence that one channel through which the effect works is task specialization (as in Peri and Sparber, 2009). The arrival of skilled immigrants drives French skilled workers towards language-intensive, managerial tasks while foreign skilled workers specialize in technical, research-oriented tasks. This mechanism manifests itself in the estimated increase in the share of foreign inventors in patenting teams as a consequence of skilled migration. Through this channel, greater innovation is the result of productivity gains from specialization.

JEL-Codes: F220, J610.

Keywords: skilled immigration, innovation, patents.

Anna Maria Mayda
Georgetown University / Washington DC / USA
amm223@georgetown.edu

Gianluca Orefice
University Paris-Dauphine, PSL / France
gianluca.orefice@dauphine.psl.eu

Gianluca Santoni
CEPII / Paris / France
gianluca.santoni@cepii.fr

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1 Introduction

Immigration continues to be a hotly debated topic in several destination countries. Policy and academic discussions have focused on different types of immigration, depending on the host country being analysed. While in the U.S. and countries with skill-points systems the literature on skilled migration is voluminous, in Europe the discussion has mostly centered around low-skilled migrants and political refugees, as they represent the largest proportion of arrivals. Yet, Europe too receives skilled migrants and their number is increasing. For example, in France the share of tertiary educated immigrants at 23% is lower than in the U.S., Canada or the U.K., but it has greatly increased, by 11 percentage points, between 1995 and 2010.[1]

Recent contributions point out that skilled immigration has greatly contributed to innovation and patenting activity (see for example Hunt and Gauthier-Loiselle 2010, Kerr and Lincoln 2010). Yet, most papers focus on the U.S. and often use aggregate data or small samples of firm-level data.[2] Europe has been largely overlooked by this literature, notwithstanding recent anecdotal evidence of the important role played by immigrants in innovation. For example, BioNTech's founder Dr.Sahin, who has developed the Pfizer Covid vaccine, is a Turkish-born scientist who lives and works in Germany. Similarly, a highly cited patent by Alcatel (France), that contributed to the improvement in the speed/cost of fiber optical cables based communication, was filed by a team of French and immigrant inventors.[3] In this paper we provide evidence on the link between immigration and innovation in the European context. We use information on the universe of French firms spanning the period between 1995 and 2010 and investigate the impact of skilled migration on patenting activity. Figure 1 summarizes the main result of the paper. It shows that, over the period 1995-2010, when the share of skilled migrants in the French population increased, the number of patents per firm went up as well as the number of foreign inventors per patent – while the size of patenting teams remained almost unchanged. Taken together, this figure provides evidence of: (i) a change in the composition of patenting teams, which over time has become more immigrant intensive; and (ii) a positive correlation between the number of foreign inventors in patenting teams and the innovation activity of firms.

– Figure 1 about here –

[1] See appendix figure A1 for data on the share of tertiary educated immigrants (over the total number of foreign born) in Canada, U.S., United Kingdom, France and Germany in 1995 and 2010.

[2] Two notable exceptions from this point of view are the seminal contributions by Burchardi, Chaney, Hassan, Tarquinio & Terry (2020) and Beerli, Ruffner, Siegenthaler & Peri (2021).

[3] Namely, Jean-Pierre Bonicel (France), Peter Elison (US), Oliver Tatan (US) and Magnus Gunnarsson (Sweden).

While figure 1 shows correlations which might be affected by the endogenous location decisions of immigrant workers, in the empirical analysis we estimate the *causal* effect of skilled migration on innovation. We instrument for the share of skilled migrants using a modified version of the shift-share instrument proposed by Card (2001) and provide evidence for the exclusion restriction by carrying out a pre-treatment trend exercise and IV validity checks (such as the plausible exogeneity test proposed by Conley, Hansen and Rossi 2012, and the IV validity check proposed by Goldsmith-Pinkham, Sorkin and Swift 2020). Also, we show that, controlling for district fixed effects, the share of skilled natives is orthogonal to the instrument-predicted share of skilled migrants, which is further evidence in favor of the exclusion restriction, since variation in the share of skilled natives is likely to capture the *economic* (hence endogenous) drivers of skilled workers' location.

We find that, between 1995 and 2010, the arrival of skilled migrants in a French district significantly raised the number of patents (controlling for district and year fixed effects). Namely, a 10% increase in the district-level share of skilled immigrants led to an increase, on average, of 2.6 patents per 10,000 manufacturing workers. We provide evidence that the effect of skilled migrants is significantly higher than the effect of skilled natives. This implies that we are not simply capturing a scale effect thereby more skilled migrants increase the size of the skilled labor force. Our results also hold when we look at the number of patents at the firm level, as a function of the district-level skilled immigrant share, and control for firm fixed effects and time-varying firm-level characteristics. We explore heterogeneity in the impact of skilled migration with respect to firm-level characteristics (as well as district-level ones). Our estimates show that high-productivity, capital-intensive and large firms are those for which the effects are stronger.

Importantly, the wealth of data available for France allows us to carry out an investigation of a new channel through which skilled immigrants are likely to affect innovation and patenting. The existing literature has shown that immigrants tend to specialize in different tasks compared with similarly skilled natives (see Peri and Sparber 2009 for low-skilled immigrants and Peri and Sparber 2011 for skilled immigrants). We combine the insight from this literature with the analysis of the effect of immigration on innovation. We point out that, given different patterns of comparative advantage of immigrant and native workers across tasks, an inflow of skilled migrants will lead to a reallocation of workers across tasks, which in turn will increase the productivity of firms, specifically in terms of innovation activity. This is indeed what we find.

We show that the pro-innovation impact of skilled immigration is driven by a within-firm reorganization of tasks – by which skilled native workers specialize in communication-intensive, managerial tasks while skilled immigrant workers in technical, research-intensive tasks. In other words each group of workers is reallocated towards the tasks in which they have a comparative advantage, which implies a higher efficiency of the innovation process driven by specialization. The structure of task-specific comparative advantage is likely driven by the lower language abilities of skilled migrants (compared to skilled natives) or by other (institutional or *de facto*) constraints they face. Indeed, it may be extremely hard for foreign born workers to access specific managerial occupations. The case of France is special from this point of view as the education system (through the *Grandes Écoles* system) is set up in such a way that outsiders (both French workers who did not attend the *Grandes Écoles* and foreign workers who studied abroad) are less likely to have access, in practice, to high-hierarchy positions (i.e *cadres*) within firms.

France does not have a large program explicitly targeted at attracting skilled migrants – like the H-1B visas program in the U.S..[4] Yet, French migration policy has drastically changed over time in the direction of favoring skilled migration. Before the oil crises of the Seventies, France had an open door policy which encouraged mostly low-skilled immigration. This was followed by severe restrictions in the 1980s and early 1990s aimed at "*immigration zéro*" (zero immigration) – exemplified by the passage of the Pasqua laws. Next came a move towards "*immigration choisie*", in the late 1990s until now, which favored skilled migration (under the initiative of Prime Minister Lionel Jospin and Interior Minister and later President Nicolas Sarkozy). More recently, the Macron administration is carrying out reforms of immigration policy aimed at discouraging asylum seekers while encouraging skilled foreign workers. These policy changes are consistent with the increase, we observe, in the share of skilled migrants to France since 1995.

The contribution of our paper to the previous literature is twofold. To the best of our knowledge, this is the first paper that explores the migration-innovation nexus using data for the universe of patenting firms in a European country.[5] This is novel and of policy interest because France does not have a skill-specific migration program and the results from this paper may shape future decisions

[4] At the European Union level, there exists the Blue Card program but it has not been successful in attracting skilled migrants, as evidenced by the low take up rate.

[5] Beerli et al. (2021) analyze the firm-level impact of immigration on innovation in Switzerland but, for this specific outcome variable, they rely on survey data which, according to the authors, "cover only a relatively small sample of firms per wave, and have some of the limitations of voluntary surveys such as reporting errors, attrition, and non-response" (page 986).

on migration policy in France. Second, this is the first paper that applies the tasks specialization idea to innovation and tests this mechanism at the micro (firm) level. We test the robustness of the task-allocation mechanism to controlling for alternative channels through which immigrants may spur innovation (i.e. knowledge diffusion and the average quality of immigrant workers), and directly check whether a positive shock in the skilled migrant labor supply makes French firms employ relatively more immigrant that native inventors in patenting teams.

The rest of the paper is organized as follows. In Section 2 we review the literature while, in Section 3, we discuss the most important changes in France's immigration policy over the last thirty years. Section 4 describes the data and shows descriptive statistics and some basic correlations in the data. Next, in section 5 we discuss the empirical strategy and how we address the endogeneity issue. Section 6 presents the baseline results at both the district (section 6.1) and firm level (section 6.2). Section 7 explores the task specialization channel as a potential mechanism, both from a theoretical and empirical point of view. The final section concludes.

2 Literature review

Most of the literature on the impact of immigration on innovation and patenting activity focuses on the U.S. and for the most part uses aggregate data.[6] Hunt & Gauthier-Loiselle (2010) exploit variation across U.S. states and find that immigrant college graduates have a positive impact on innovation and this is because they disproportionately hold STEM degrees. Similarly, Chellaraj, Maskus & Mattoo (2005) document that the presence of foreign graduate students has a positive impact on future patents in the U.S.. Kerr & Lincoln (2010) focus on the effects of H-1B visas on patenting activity of ethnic inventors. They look at whether shifts in national H1-B admissions are associated with stronger or weaker innovation in states/cities/firms that are very dependent on the program relative to less dependent ones. The authors carry out the analysis, for the most part, at the city level.[7] More recently, Burchardi et al. (2020) estimate a positive causal impact of immigration on innovation across U.S. counties based on information on their ancestry composition and patenting of local firms.

[6] A firm level perspective is used in the literature on innovation and import competition. Bloom, Draca & Van Reenen (2015) and Autor, Dorn, Hanson, Pisano & Shu (2020) use firm level data for EU and US respectively to test the innovation effect of import competition shocks. Bloom et al. (2015) find that an increase in Chinese import penetration is associated with a 3.2% increase in the patenting activity of European firms over the period 1978-2007. Differently, Autor et al. (2020) show a decline in the firms' patenting activity in sectors facing greater import competition; with this effect magnified for initially less productive and less capital-intensive firms.

[7] The firm-level analysis in Kerr & Lincoln (2010) is for a small sample of companies (77 firms).

Akcigit, Grigsby & Nicholas (2017) use data on the historical settlement of EU immigrants across US states, and the areas of technological advantage of EU countries, to study the effect of immigrant inventors on long-run innovation activity of US states. The authors show that the technology areas in which immigrant inventors were more prevalent in the period 1880-1940 experienced faster growth in patenting in the post-1940 period. Importantly, they also show that immigrant inventors were more productive than native born inventors. Similarly, using cross-country data, Bahar, Choudhury & Rapoport (2020) focus on the innovation effect of immigrant inventors through knowledge diffusion from their countries of origin, and show that the host countries are more likely to specialize in patents on a specific technology when the countries of origin of the foreign inventors specialize in that same technology. Moser, Voena & Waldinger (2014) look at the emigration of German Jewish scientists who fled the Nazi regime and find overwhelming evidence of a positive and significant contribution of German immigrant scientists to the US inventions during the twentieth century. An important recent contribution to the literature is the work by Doran, Gelber & Isen (2022), which exploits the H-1B visa lottery in fiscal years 2006 and 2007 to analyze the effects of H-1B visas on patenting and overall firm employment. This paper finds no evidence of an effect on patenting and at most a moderate effect on overall employment in the firm. However, lotteries in 2006 and 2007 were for a selected (and limited) sample of applications/firms. For Europe, Parrotta, Pozzoli & Pytlikova (2014) analyze the connection between worker diversity within a firm and its patenting activity using data for Denmark. Their results suggest that ethnic diversity leads to more patenting. Finally, Bratti & Conti (2018) find no evidence of either positive or negative effects of migrants to Italy on innovation; which is consistent with the fact that most immigrants to Italy are low-skilled. Finally, more recently, Beerli et al. (2021) find that highly-educated cross-border workers to Switzerland increase the innovation of skill-intensive incumbent firms.

To conclude, the bulk of the literature on immigration and innovation focuses on the U.S. and for the most part uses aggregate data. Our paper carries out a firm-level analysis for a European country, France, and explores a new mechanism of impact, namely task specialization, in the migration-innovation nexus.

3 France's immigration policy: An Overview

The period we analyze is characterized by several important changes of immigration policy in France. Looking back in time before our period of analysis, right after World War II, France experienced a great deal of economic permanent migration, mostly low-skilled, especially from its previous colonies in Northern and sub-Saharan Africa. With the oil shocks in the 1970s, barriers to migration went up, although family reunification and asylum seekers' arrivals implied that immigration to France did not stop. Table A1 shows the constant increase in the share of immigrant workers residing in France over the last forty years (based on French Census data).

In the 1980s and early 1990s, political backlash by public opinion, especially against Muslim immigrants, led to the rise of Jean-Marie Le Pen's extreme-right National Front party as well as a consensus – of politicians across the political spectrum – about the need for "*immigration zéro*" (zero immigration) in France. The right-wing government that came into power in 1993 made zero immigration a policy reality by passing the Charles Pasqua laws, which aimed to block the remaining legal immigrant flows to France in a variety of ways.

The end of the 1990s saw the beginning of a major policy shift. As Prime Minister, Socialist Lionel Jospin passed the 1998 law on immigration which created a special status for scientists and scholars and, in general, made it easier for certain highly skilled professional categories to come to work in France.[8] Next, in the mid-2000's, Interior Minister and later President Nicolas Sarkozy further shifted towards selective immigration by carrying out the policy of "*immigration choisie*". This is a clear departure from previous policies of zero immigration. The goal of "*immigration choisie*" is to: 1) fight irregular migration; 2) decrease family migration; 3) increase labor migration targeting particular migrants and encouraging skilled migration. From a political economy point of view, immigration choisie tries to reconcile anti-immigration public opinion with the need of the French economy for certain types of workers. Indeed, two job categories are identified as being in especially low supply: "low qualified jobs in the service sector (to families, elders, children, disabled people...), and highly qualified jobs in the service sector and industry (white collars and skilled technicians in the construction and education

[8] Bertossi (2008) explains: "Between 1998 and 2004, "opposability of the labour market situation" was suspended by decree (circulaire) for the IT sector (with a minimum gross salary condition of 2,250 Euros), after the ministries of Labour and of Interior responded to claims by the IT Professional Organisation that IT specialists were needed to prepare computer systems to the New Millennium and the Euro. The immigration procedure was also simplified. Around 10,000 IT workers came to France, under both temporary and permanent residence permits – against 35,000 IT workers needed according to estimates of the "Syntec Informatic" professional organisation (Le Monde 2001). Another decree from the Ministry of Labour in March 2004 facilitated and shortened the procedure for foreign 'white collars'."

sectors)." See Bertossi (2008), page 9.[9].

In Sarkozy's 2006 policy of "*immigration choisie*", immigrants' labor-market access is conditional on the country of origin: There was total freedom of movement and access to the labour market – including to some jobs usually closed to non-nationals (such as in the education and health sectors) – for immigrants from the European Union, Common European Economical Space, and Switzerland. However, France restricted access to its labor market for immigrants originating from "new" EU Member States of the 2004 and 2007 EU enlargements with exceptions for 150 occupations (and immigrants from Cyprus and Malta).[10] France applied temporary restriction measures until May, 1, 2009 for 8 of the 2004 new member states, and until January, 1, 2012 for Bulgaria and Romania.[11]

To conclude, France's approach to immigration has shifted from very restrictive – in terms of the size of immigrant flows – in the 1970s up to 1997, to less so in the last twenty-five years. French immigration policy has also moved towards a much greater emphasis on skills and migrants' selection. These policy developments are consistent with the changes in skilled immigrant flows we observe in the data, which is what we turn to next.

4 Data and descriptive evidence

Our empirical analysis uses four data sources: (i) matched employer-employee French data (*Déclaration Annuelle des Donnée Sociales* – DADS), (ii) balance sheet information (FICUS/FARE), (iii) firm level patenting data sourced by Orbis and (iv) historical patenting data for French districts in the 19^{th} and 20^{th} century sourced by INPI (National Industrial Property Institute). Summary statistics of the main variables used in the district-level and firm-level analyses are presented in table 1.

– Table 1 about here –

The DADS is an administrative database collected by the National French Statistics Office (INSEE) containing contract level information (i.e. firm-worker match) for the universe of French workers over

[9]https://www.ifri.org/sites/default/files/atoms/files/cespi08.pdf

[10]The Accession Treaty of 2003 gave the possibility to the "old" member states to temporarily restrict (for a maximum of 7 years) the access to their labor markets to citizens from "new" member states, with the exception of Malta and Cyprus. These restrictions were temporary and followed a three-step formula (2+3+2). During a first period of two years (May 1st, 2004 to April 30th, 2006), each old member state could regulate the access of workers from new member states (except for Malta and Cyprus). This initial temporary restrictions could be extended for an additional 3 years (until April 30th, 2009). A last period of temporary restrictions were allowed, upon approval of the European Commission, only in the case of proven cases of domestic labor market disturbances.

[11] Third country nationals are ruled by bilateral migration agreements, but in general former French colonies are penalized by immigration choisie (see Bertossi 2008).

the period 1995-2010. All legal wage-paying entities in France report information on their employment structure to the DADS. Hence, for each worker in the sample we have information on annual earnings, total number of hours worked, job spell in the firm, gender, age, district of residence and occupation (available at both 2- and 4-digit of the PCS classification).[12] Each worker is associated to an employer (identified by a unique code called SIREN), allowing us to have detailed information on the employment structure of each firm.

Importantly for our empirical strategy, DADS data allows us to calculate the number (and the share) of migrant and native workers in each French district in a given year.[13] Two variables from DADS data are used to define the immigrant status of a worker in the period 1995-2010: (i) a direct indicator of whether the worker is French or foreigner (variable called *etrang*), and (ii) a variable indicating the worker's district of birth (variable called *depnai*) with a specific code for foreign-born workers. Based on the quality of these two variables, we adopt *etrang* for the period 1995-2008 and *depnai* for the years 2009-2010 to calculate the number of immigrant workers in each French district. Indeed, a high number of *etrang* missing observations in the years 2009-2010 led us to use the department of birth (*depnai*) to recover the immigrant status of workers in the years 2009-2010. Combining these two different variables gives rise to measurement error in the number of migrants, because one variable refers to nationality while the other to country of birth. Although year fixed effects will control for this discontinuity in the definition of migrant workers around 2008, in all the baseline tables of results we show robustness checks using the sub-period 1995-2008 for which only the direct measure of immigrant status (*etrang*) has been used to calculate the number of immigrant workers in the district.

The education of workers is not directly available from DADS data.[14] We infer the skill level of workers from their occupation. Namely, we employ a specific occupation-education matching based on the International Standard Classification of Occupations ISCO, that assigns a specific education level to each one-digit ISCO occupation code.[15] Details on how each specific occupation is matched to an

[12]The PCS (i.e. *Professions et Catégories Socioprofessionelles*) is the French classification of workers' occupation made available by DADS at two- and four-digit aggregation levels. An example of a two-digit occupation is "*Ouvriers Qualifiés de type industriel*". An example of a four-digit occupation is "*Plate-formistes, controleurs qualifiés de matériel électrique ou électronique*".

[13]Unfortunately, DADS does not provide information on the specific country of origin of immigrant workers in French firms. In France, in 2010, the origin countries with the highest share of skilled immigrants were: Algeria (9.8% of total skilled immigrants in France), Morocco (9.6%), United Kingdom (5.9%), Germany (4%) and Belgium (3.6%). Source IADB database.

[14]The level of education of workers is available only for a sub-period starting in 2009.

[15]The specific ISCO based occupation-education correspondence table is available here: `https://www.eurofound.europa.eu/surveys/ewcs/2005/classification`. The conversion from the PCS French occupation classification into 1-digit ISCO has been done manually without loss of information.

education level are reported in table A2. However, the matching based on 1-digit ISCO categories may be imprecise, and some skilled workers may be classified as low skilled simply because the 1-digit ISCO code they belong to is too broad. Hence, to reduce concerns for the imperfect occupation-education match, we use "*techies*" workers as an alternative proxy for skilled workers. In line with Harrigan, Reshef & Toubal (2021) we define techies workers as those in PCS occupation 47 ("*Techniciens*") and 38 ("*Ingénieurs et cadres techniques d'entreprise*"). Based on these two definitions, we compute the share of migrant and native skilled workers in each district-year for 94 French districts over the period 1995-2010.[16] Our district-level sample includes 1,504 observations, while the firm-level sample includes 51,704 firm-year observations. The average share of skilled migrant and native workers is 2.7% and 35%, respectively (see table 1).

Using the firm identifier (SIREN) we merge DADS with FICUS/FARE data, a firm-level database collected by the INSEE and providing information on the balance sheet of French firms. Specifically, the FICUS/FARE dataset provides information on the value added, sales, total employment, capital, sector of reference, intermediate inputs and other balance sheet information for the universe of French firms over the period 1995-2010. This dataset is used to compute three district-year control variables included in all district level specifications: (i) total value added in the district (to control for the economic size of the district), (ii) the capital-value added ratio (controlling for the capital intensity of the district) and (iii) the average value added per firm (controlling for the average productivity of firms in the district). FICUS/FARE data are also used to compute firm-level control (i.e. value added, capital intensity and value added) for firm-level regressions.

Data on firm level innovation activity come from the Bureau Van Dijk Orbis database, which links global patents to the universe of publicly listed companies and corporate groups worldwide.[17] Table 1 shows the large dispersion in patenting activity across French firms: the average number of active patents per firm is 8, with standard deviation 53.9 (number of patents ranging from 0 to 4775). We merge patent ownership data for French active firms in Orbis to DADS and FICUS/FARE using the common firm identifier SIREN.[18] Information on the historical innovation activity of French districts

[16] Since data on past settlement of immigrants – which is used to build the instrumental variable in section 5.1 – are not available for overseas French districts, we limit our analysis to 94 mainlands' districts.

[17] Although Orbis includes over 130 million companies across the world, smaller firms tend to be unrepresented in the database. Coverage may also differ from country to country due to different business registers filling requirements. Kalemli-Ozcan, Sorensen, Villegas-Sanchez, Volosovych & Yesiltas (2015) provides a full assessment of representativeness of Orbis by country; for France, firms in the database account for over 70% of aggregate output over the period 1999-2012 (80% since 2008). For more detailed information on the database see `http://www.bvdep.com`.

[18] After merging we track 4,729 firms having at least one active patent over the period. These firms represent 42% of

(used to control explicitly for the pre-trend) is publicly accessible via the INPI.[19] The database includes detailed information on more than 400 thousand patents from 1791 to 1902.

Next we focus our attention on the change in, respectively, the share of skilled migrants and log(patents) per capita between 1995 and 2010. The share of skilled immigrants increased in the largest French cities, such as Paris (*Ile de France*), Lyon (*Rhône*) and Toulouse (*Haute Garonne*), and in south-coastal districts. Instead we observe a reduction in skilled immigrants (over population) in northern and western districts. In terms of patenting activity, the districts of the *Auvergne-Rhône-Alpes* region experienced a marked increase in patents *per capita*. Finally, a simple scatterplot of the change in (log) patents on the change in the share of skilled migrants, between 1995 and 2010, shows a positive and significant correlation across districts (see figure 2).

– Figure 2 about here –

5 Empirical strategy

The goal of the empirical analysis is to estimate the impact of the share of skilled migrants in each local labor market (here approximated by a French district or *département*)[20] on the patenting activity of both French districts (results discussed in section 6.1) and firms (results discussed in section 6.2). The two empirical specifications, respectively at the district and firm levels, are the following:

$$Y_{dt} = \theta_d + \theta_t + \beta_1 MigSh^{High}_{dt} + \mathbf{X}_{dt} + \epsilon_{dt} \tag{1}$$

$$Y_{i\in d,t} = \theta_{id} + \theta_{st} + \delta_1 MigSh^{High}_{dt} + \mathbf{X}_{it} + \epsilon_{idt} \tag{2}$$

where the subscript d, i, s and t stand respectively for district, firm,[21] firm's sector and year. The dependent variable is the (logarithm of) active patents in each district (eq. 1) and firm (eq. 2).[22]

manufacturing value added in France.

[19] https://www.inpi.fr/fr/base-brevets-du-19eme-siecle.

[20] We approximate the local labor market with a French *département* rather than a smaller geographical unit (such as commuting zones or *zone d'emploi*) for two reasons. First, to build the IV we need information on the geographical distribution of immigrants back in 1980 and this is available at the district (not commuting zone) level. Second, using smaller geographical units may imply a large number of zeros when we look at the change in the share of skilled immigrant workers and patenting activity of firms.

[21] Only few French firms have production establishments in different districts. In these few cases, we consider the district of the largest plant as the district of the firm as a whole.

[22] In a set of robustness checks reported in table 6 and appendix section B we alternatively use: (i) first- and long difference approach (as in Bloom et al. 2015), (ii) the 1-year change in the number of patents per 100,000 people in the district as in Burchardi et al. (2020), and (iii) the number of patents per worker.

The key variable of interest is the district-level share of skilled migrant workers (over total number of workers) denoted by $MigSh_{dt}^{High}$. We include a full set of fixed effects θ_d, θ_t, θ_{id}, θ_{st} and control variables $\mathbf{X}_{dt}$ and $\mathbf{X}_{it}$. To address the problem of zeros in the number of patents, we use the inverse hyperbolic transformation.

Although the information on the number of immigrant workers is also available at the firm level, our main explanatory variable is at the *district* level. The reasons are that: first, we can only construct the instrument at the district level – since we lack information on firms' workforce composition by origin country in the pre-1995 period – so ultimately the variation we exploit is at the district level; second, the ethnic network idea on which the instrument is based is more reasonable at the district level; third, endogeneity of the immigrant share is likely more severe at the firm level.[23] By using district-level skilled migrant shocks, we make the implicit assumption that they are correlated with firm-level decisions. Table A3 empirically supports this implicit assumption. Positive changes in the share of skilled immigrants in the district cause an increase in the number of immigrant skilled workers employed in the firm (2SLS approach used).

5.1 Endogeneity and Identification Strategy

In assessing the causal impact of skilled immigrant workers on the patenting activity of French districts and firms, we face two empirical challenges. First, unobserved district- and firm-specific variables (such as productivity shocks) can shape the settlement of skilled workers across districts and firms, and affect the patenting activity of firms (*omitted variables*). Second, the patenting activity of firms in each district can directly affect the settlement of skilled workers across districts (*reverse causality*). These issues imply biased OLS estimates (endogeneity). The inclusion of district/firm fixed effects in district/firm specific regressions considerably reduces the omitted variable concern. However, time-varying district or firm-specific unobservable factors may still be an issue and call for the use of an IV approach in order to address any remaining endogeneity concern.

We adopt the shift-share methodology to build the IV for the share of skilled immigrant workers in each local labor market. Using French Census data, we first calculate the share of *high skilled* immigrant

[23] For completeness, we run a specification with the firm-level immigrant share instrumented with the district-level IV.

workers (SM) by group of origin (o) residing in each French district (d) in 1980 as follows:[24]

$$sh^{SM}_{d,o,1980} = \frac{SM_{d,o,1980}}{\sum_d SM_{d,o,1980}} \quad .$$

We obtain the *imputed* number of skilled immigrant workers in the district by multiplying the time-varying aggregate number of immigrants of each country of origin (M_{ot}) by the 1980 shares of skilled immigrants across districts ($sh^{SM}_{d,o,1980}$).[25] The predicted number of skilled immigrants ($\widehat{SM}$) in district d is given by the following equation:

$$\widehat{SM}_{dt} = \sum_o sh^{SM}_{d,o,1980} M_{ot} \quad . \tag{3}$$

Finally, the instrument for the share of skilled immigrants in district d is the *imputed* number of skilled immigrants divided by the *imputed* total population, which is constructed total number of *imputed* immigrants and natives $\left(\widehat{SM}_{dt}/(\widehat{N_{dt}} + \widehat{M_{dt}})\right)$.[26] [27]

To get a sense of where skilled migrants settle, and the type of endogeneity which is implied, we investigate the link between the geographical distribution of skilled natives and migrants across French districts. We were expecting to find that the two sets of skilled workers tend to co-locate (in better performing districts). Yet what we find is that, controlling for district and year fixed effects, there is a negative correlation between the two series (see columns (1)-(3), table 2). The correlation is significant except in the long difference specification. Importantly, once we instrument the skilled immigrant share using the shift-share IV, the negative correlation disappears (see columns (4)-(6), table 2).[28] Since the geographical distribution of skilled natives is likely to capture the most important economic drivers of skilled workers' locations, we interpret these results as supporting evidence of the validity of our instrumental variable. In what follows we show additional tests aimed to support the validity of the IV (pre-treatment trend exercise, validity test based on Rotemberg weights, and the test of plausible exogeneity).

[24]The French Census data group immigrants' origin into 5 macro-regions - see table A4 for the composition of each macro-region of origins.

[25]The total number of immigrants in France by origin, M_{ot}, is constructed by adding origin-specific immigrant inflows from OECD-IMD data to the initial stock of immigrants by origin in 1980 (from the French census data).

[26]The imputed number of natives has been computed using a similar approach, i.e. allocating the total number of French workers based on the cross-district distribution of natives in 1980.

[27]We cannot use an IV à la Burchardi et al. (2020) due to the lack of data on ancestry in the case of France.

[28]See also figure A2.

– Table 2 about here –

Pre-treatment trends exercise. In table 3 we show that there is no correlation between the pre-1995 trends in districts' innovation activity (using changes in the number of patents over four twenty-year time windows) and the 1995-2010 difference in the imputed share of skilled immigrants (IV). This qualitatively supports the absence of unobserved (and endogenous) factors that shaped the patenting activity of French district and the current variation in the imputed share of skilled immigrants.

Validity test based on Rotemberg weights. One key assumption for the overall validity of a Bartik (shift-share) instrumental variable is the orthogonality of the initial geographic distribution of immigrants across local labor markets, in particular for those groups of origins that have large impact on the identification of the 2SLS estimator. Here we follow the approach suggested by Goldsmith-Pinkham et al. (2020) and calculate the Rotemberg weights associated to each macro-group of immigrants' origins - see table A4 for the composition of each macro-region of origins. Not surprisingly, the macro-group covering the largest set of origins (i.e. Other origins) accounts the most for the overall identification of the shift-share IV (0.9 Rotemberg weight).[29] Other origins are less important for the identification of the shift-share IV.[30] In table 3 we test the exogeneity of such origin-specific migrant shares, and regress the trend in the patenting activity of districts during four different pre-1995 periods on the change in each origin-specific shift-share IV in the 1995-2010 period. Results reported in table 3 show that the variation in the origin-specific imputed share of immigrants in the period 1995-2010 is not correlated with a more intense patenting activity of firms across districts in the years before 1995. Alternatively, in table A5 we test the correlation between the pre-1995 trend in the patenting activity of firms and the initial settlement of immigrant by macro-origin. The absence of correlation suggests that the initial settlement of immigrants (by origin) across French districts does not reflect the innovation activity of firms across districts. These pre-trend tests supports the overall validity of our IV.

– Table 3 about here –

Alternative Instrumental Variable. As discussed in Borusyak, Hull & Jaravel (2021), the exogeneity of the aggregate shift component in eq. 3, M_{ot}, can guarantee the validity of the shift-share

[29] The other origin group includes: Argentina, Australia, Brazil, Chile, Colombia, Haiti, Mexico, Russia, United States, Venezuela, Canada, Other Oceania and Other American.

[30] We also calculate the effect of skilled immigrant workers by group of origin on the patenting activity of districts. We find a 2SLS coefficient 0.111 when using Other origins, 0.120 when using African countries, 0.125 for Eastern Europe & Central Asia origins, 0.135 for Asian origins and 0.154 for European origins.

IV. If unobserved shocks to a French district attract most immigrants from a specific origin, then the aggregate numbers are not exogenous. To address this concern, as a robustness check, we propose an alternative shift-share IV where the aggregate shifts are constructed as a function of immigrant inflows to other countries, which by construction are orthogonal to origin-specific ties to France. We regress the bilateral immigrant inflows to France (PPML estimator) on: (i) the bilateral immigrant inflows to neighboring countries and (ii) a set of origin and year fixed effects.[31] We then use the predicted values of this regression, net of any origin- and time- specific factors (estimated fixed effects), as the aggregate shift in eq. 3.[32]

Plausible Exogeneity. As an alternative test of the validity of our IV, we check the robustness of the coefficient of interest ($MigSh_{dt}^{High}$) to possible deviations from perfect exclusion restriction validity. Namely, we apply the plausible exogeneity test proposed by Conley et al. (2012) allowing for possible deviations from exact validity of the exclusion restriction (i.e. non-zero correlation between the IV and the error term in equations 1 and 2). First, we relax the exclusion restriction and assume a non-zero correlation between the IV and the error term, i.e. $\gamma \neq 0$.[33] A reasonable approximation of the degree of correlation between the IV and the error term (i.e. extent of deviation from the perfect validity of the exclusion-restriction) can be obtained as discussed in van Kippersluis & Rietveld (2018). We identify the sub-groups of districts for which the IV does not predict the endogenous variable ($MigSh_{dt}^{High}$).[34] This sub-group of districts represents the ideal set to test the exclusion restriction. Indeed, if the correlation between the IV and the endogenous variable is zero, the direct effect of the IV on the patenting activity of districts and firms should be zero too. So, we regress the patenting activity of districts and firms on the imputed share of skilled immigrants for this sub-group of districts only. The estimated coefficients γ from this zero-stage regression are reported in table A6. Reassuringly, these coefficients are small and not statistically different from zero, suggesting the absence of a direct effect of the IV on the dependent variable and hence supporting the validity of the exclusion restriction.

These coefficients are also reasonable values of γ to be used in the plausible exogeneity test (van Kippersluis & Rietveld 2018). We follow Conley et al. (2012) and estimate the union-of-confidence

[31] France neighboring countries are Spain, Belgium, Luxembourg, Germany, Switzerland and Italy.

[32] A similar approach has been used by Bianchi, Buonanno & Pinotti (2012).

[33] See Conley et al. (2012) section 4.

[34] We run district specific regressions checking the conditional correlation between the IV and the observed share of skilled immigrants, and select those districts for which such a correlation is not statistically significant (i.e. 14 districts).

intervals by assuming γ obtained as discussed above. In table A6 we report the 90% confidential intervals obtained by applying the Conley et al. (2012) test for the plausible range of γ. The confidential intervals do not cross the zero, so our baseline results (discussed in the next section) are robust to plausible deviations from the exclusion restriction. In other words, the sign of coefficient β_1 in eq. (1) and δ_1 in eq. (2) is robust to deviations from the perfect validity of the exclusion restriction.

6 Immigration and innovation nexus: baseline results.

This section shows the effect of exogenous skilled migrant labor supply shocks on the innovation activity of French districts (section 6.1) and firms (section 6.2).

6.1 District-level evidence

We start our empirical analysis by exploiting variation across districts and time. With the aim of including the share of both *immigrant* and *native* skilled workers in the same regression, we slightly modify eq. (1) and include region rather than district fixed effects.[35] This allows us to instrument the share of both migrant ($MigSh_{dt}^{High}$) and native ($NatSh_{dt}^{High}$) skilled workers (district-specific controls $\mathbf{X}_{dt}$ always included).[36] Both migrant and native skilled workers have a positive and significant effect on the patenting activity of districts (see table 4). The point estimate associated to the share of skilled migrants is larger than for high skilled natives and this difference is significantly different from zero when we use the alternative proxy for the skill level of workers (techies) as in columns (3)-(4).

– Table 4 about here –

We now move to our preferred district-level specification where we include district fixed effects θ_d as in equation (1). We therefore exploit the pure within-district variation in the number of patents and share of skilled immigrants. When we include district fixed effects, we cannot nor need to control for the high-skilled native share for the following two reasons. First, the imputed number of high-skill natives $\widehat{N_{dt}}$ (i.e. the instrument for the share of skilled natives) is almost entirely explained by district and year

[35] French regions are geographical units including on average five districts.

[36] To construct the IV for the share of skilled native workers in each district, we calculate the share of *high skilled* natives (N) in each district in 1980 $sh_{d,1980}^{N} = \frac{N_{d,1980}}{\sum_d N_{d,1980}}$; next we impute the number of skilled natives in district d at time t by multiplying the share $sh_{d,1980}^{N}$ by the aggregate level of skilled native workers in France N_t. Finally, we instrument the share of skilled natives with the imputed share of skilled natives in the district $\left(\widehat{N}_{dt}/(\widehat{N_{dt}} + \widehat{M_{dt}})\right)$.

fixed effects – see the R-squared in the regression of the instrumented number of natives on district and year fixed effects in table A7. This produces a weak first stage, if we include and instrument for the share of skilled natives, in the specification with district and year fixed effects. Importantly, omitting the share of natives from these regressions does not imply a bias in the estimation of $MigSh_{dt}^{High}$. As already shown in the last three columns of table 2, controlling for district and year fixed effects, the instrumented distribution of skilled immigrants is orthogonal to the distribution of skilled French workers. This implies that omitting the latter does not create an omitted variable bias.

Results from the estimation of equation 1 are reported in Table 5. OLS results are reported in columns (1) as a benchmark, 2SLS estimates in columns (2)-(7), IV-PPML estimator in column (8) and the specification with the alternative IV based on immigrant inflows to other countries in column (9). The share of high skilled native workers, $NatSh_{dt}^{High}$, is included in columns (1) and (3) to test the robustness of the coefficient associated to the share of high skilled immigrants, but it is not instrumented for the lack of within variation in the imputed number of skilled native discussed above. In columns (4)-(5) we include the set of controls $\mathbf{X}_{dt}$ capturing the effect of the capital intensity, average productivity and total value added of the district. The value added per firm accounts for any productivity shock in the district, while total value added controls for any change in the economic size of the district. Across all specifications the effect of skilled immigrant on the patenting activity of French districts is positive and statistically significant. In particular, by using point estimates in column (3) of table 5 we can conclude that a 10% increase in the average share of skilled immigrants in the district implies an increase of 2.6 patents per 10,000 manufacturing workers.[37] In column (5) we show results using the 1995-2008 sub-period to avoid the change in the definition of migrant occurred in 2009-2010 (discussed in section 4). Reassuringly, the coefficient of interest is identical, suggesting absence of measurement error due to the change in the variable of reference to identify immigrant workers. Compared to OLS coefficient in column (1), 2SLS estimations show a larger effect of skilled immigrants on the patenting of French districts. This is due to the omitted variable problem in OLS: unobserved district specific shocks (such as agglomeration, housing price change, gentrification) are positively correlated with the patenting activity of districts (Lobo & Strumsky 2008, Carlino & Kerr

[37]The average share of skilled immigrants in a French district is 1.9% – see table 1. So, a 10 percent increase in the share of skilled immigrant in the average district corresponds to a 0.19 p.p. increase. Using the point estimate of column (3) of table 5, such a 0.19 p.p. increase in the share of skilled immigrants implies a $(0.19 \times 0.119) \times 100 = 2.26$ percent increase in the number of patents in the district. This equals to 6.96 additional patents for the average district (having 308 patents), and corresponds to 2.6 patents per 10,000 manufacturing workers in the average district hosting 27,048 workers – see table 1.

2015) but negatively correlated with the settlement of immigrants (Accetturo, Manaresi, Mocetti & Olivieri 2014).[38]

– Table 5 about here –

In the bottom part of table 5 we show the first stage coefficients (highly significant) and F-stats (above the rule of thumb of 10). Our results also hold when we construct the IV using the geographical distribution of immigrants in 1975 and 1990 (see columns (6)-(7)). In the last column of Table 5 the shift-share IV is based on immigrant inflows to other (neighbour) countries, and results remain qualitative unchanged.

In table 6 and appendix section B, we propose a battery of checks aimed at testing the robustness of our baseline results reported in table 5 at the district level. We construct an alternative proxy for skills based on the number of workers in techies occupation (see column 1 in table 6, and table B1 for more results). We define the outcome variable as the number of patents *per worker* (column 2 in table 6, and table B2 for more results). We report results using the specification à la Burchardi et al. (2020), in which the dependent variable is the 1-year change in the number of patents per 100,000 people in the district (see column 3 in table 6, and table B3 for more results). We use, as key explanatory variable, the share of skilled immigrants over total skilled workers (see column 4 in table 6, and table B4 for more results). We adopt a reduced form approach and plug the instrumental variable directly in an OLS specification (see column 5 in table 6, and table B5 for more results). In columns 6-7 of table 6 (and in tables B6 and B7 for more results) we use a first- and long difference approach with the dependent variable expressed in log-difference (as in Bloom et al. 2015). The advantage of the first- and long-difference approach is the possibility of controlling explicitly for pre-trends in the patenting activity of districts, captured by the historical changes in the patenting activity of immigrant and native workers over the XIX^{th} century. Finally, in column (8) of table 6 we test the robustness of our IV and baseline results by excluding francophone countries from the sample of origins in the shift-share instrumental variable.

– Table 6 about here –

[38] Accetturo et al. (2014) find that immigration reduces housing price growth in a specific city-district (vis-a-vis the rest of the city). Authors show evidence that this pattern is driven by native moving from immigrant-dense districts towards other areas of the same city.

6.2 Firm-level evidence

In this sub-section we focus on firms, and use the number of active patents of firm i located in district d at time t as the dependent variable. The main explanatory variable $MigSh_{dt}^{High}$ remains at the level of the district (as explained in section 5).[39] Firm-district fixed effects θ_{id} control for time-invariant characteristics of a firm located in a given district.[40] Sector-year fixed effects θ_{st} account for time-varying shocks (i.e. policy) that affect the patenting activity of French firms in a given sector. The set of firm-specific controls X_{it} in eq. (2) includes: (i) the value added per worker as a proxy for the time-varying productivity of the firm (in log), (ii) the ratio between physical capital and value added as a proxy for the capital intensity of the firm (in log), and (iii) the total value added of the firm (in log) to control for the size of the firm.

Results from firm-level estimations are reported in table 7. We find overwhelming evidence of the positive and significant effect of skilled immigrants on the patenting activity of French firms. The result is robust across specifications: OLS (column 1), baseline 2SLS (columns 2-3), robustness check using shorter time period 1995-2008 (columns 4), alternative IV based on initial immigrant shares in 1990 (column 5) and 1975 (column 6). The firm-level results are also robust to the alternative proxy for workers' skills (the share of migrants in techies occupations) in columns 7-8. First-stage statistics are reported at the bottom of table 7 and indicate both the relevance of the IV and the absence of weak-instruments concerns (F-stat well above the rule of thumb of 10). In the last two columns of table 7 we test the robustness of the 2SLS results to using immigrant flows to other (neighbour) countries for the shift component of the IV. Results remain qualitatively unchanged.

– Table 7 about here –

In the vein of what Autor et al. (2020) argue in the context of import competition,[41] the effect of skilled immigration may vary with firm characteristics. To explore heterogeneous effects, we interact the share of tertiary educated immigrant workers in the district with the following initial characteristics of the firm (H_{i,t_0}): (i) productivity (dummy equal to one if firm's productivity at t_0 above 75^{th} percentile); (ii)

[39]Table A3 shows the strong positive effect of exogenous district-specific shocks to the share of tertiary educated immigrants on the number of tertiary educated immigrants in the firm. Moreover, in table C1 we show a robustness check using the share of tertiary educated immigrants in the firm as the main explanatory variable (instrumented by the district-specific shift-share IV) and the results hold.

[40]Since some firms change location, firm-district fixed effects are preferable to firm fixed effects.

[41]Autor et al. (2020) show that the patenting activity of firms with an initial weaker competitive position are more likely to be hurt by foreign competition. Highly productive and capital-intensive firms have smaller reductions in their innovation activity when hit by import competition shocks.

capital intensity (dummy equal to one if firm's capital intensity at t_0 above 75^{th} percentile); and (iii) size (dummy equal to one if firm's value added at t_0 above 75^{th} percentile). As an instrument for the interaction term $MigSh_{dt}^{High} \times H_{i,t_0}$, we use the shift-share IV multiplied with the firm characteristics H_{i,t_0}. Results in table 8 clearly show that large, capital intensive and high-productive firms benefit the most from positive shocks in the share of skilled immigrants.

– Table 8 about here –

In table 9 and appendix section C we propose a battery of robustness checks of the firm-level results. First, in column (1) of table 9 (and in table C1 for more results) we replicate the baseline results using the *firm-level* share of skilled immigrants as the main explanatory variable, instrumented with the district-specific shift-share imputed immigrant share. Our results hold. Second, in column (2) of table 9 (see table C2 for OLS results) we test whether the results are driven by big cities. In particular, we explore the heterogeneous effect of skilled immigrants on the patenting activity of firms in districts with big cities such as Paris, Marseille and Lyon. Our results are not driven by firms in big cities. In column (3) of table 9 we also test the robustness of the IV and firm-level results by excluding francophone countries from the sample of origins in the shift-share instrumental variable. Finally, the settlement of skilled immigrants across sectors is likely to be persistent over time, and our baseline results can be driven by specific sectors. To address this concern, in figure C1 we show the 2SLS point estimates for the share of skilled immigrants by excluding one sector at time from the estimation sample. Coefficients are all around our baseline estimate, 0.047, in table 7, column (2). This suggests that the baseline results are not driven by a specific sector.

– Table 9 about here –

7 Immigration and innovation nexus: The mechanism.

So far we provided robust evidence of a positive causal effect of skilled immigration on the innovation activity of French firms and districts. The goal of this section is to explore the mechanism of impact, focusing in particular on the task-reallocation channel proposed by Peri & Sparber (2009). We first develop a theoretical framework to illustrate how the task-allocation mechanism works (section 7.1). Next, in section 7.2, we provide empirical evidence of the task-allocation mechanism. Finally, in section

7.3, we show that the results on task allocation are robust to controlling for other channels of impact, specifically knowledge diffusion through immigration and the average quality of skilled immigrants at destination.

7.1 Immigration, tasks allocation and patenting activity: theoretical motivation

This section proposes a mechanism of impact, in the migration-innovation nexus, in the vein of task re-allocation as in Peri & Sparber (2009). The basic intuition is that, because of migrants' lower language/communication skills or other institutional constraints, skilled immigrants tend to have a comparative advantage in technical, research-intensive tasks (such as in STEM), while skilled natives tend to have a comparative advantage in language-intensive, managerial occupations. A positive shock in the skilled migrant labor supply in the district will push firms to allocate native and immigrant workers based on their comparative advantage. This will spur productivity in innovation activity, due to gains from specialization, and increase the number of patents produced in the firm. The case of France is particularly interesting in this respect because many top-hierarchy positions in France are devoted (in some cases *de jure*, in other circumstances *de facto*) to individuals having attended the so called *Grands Écoles*, excluding the possibility for skilled immigrants that completed their education cycle abroad to access top-hierarchy positions (i.e. *cadres*) in private firms or public institutions.

We consider each firm in France in year t producing patenting (i.e. innovation activity)[42] by combining the services of two occupations: (i) purely technical research oriented tasks (T), and (ii) managerial tasks (M).[43] The managerial tasks require sufficient knowledge of the product/sector of the firm and proficiency in language and team-managing skills. Purely technical tasks require mostly cognitive and scientific skills. The services of both occupations o (with $o = T, M$) can be produced by combining tertiary educated immigrant (L_o^I) and domestic workers (L_o^D), which are assumed to be imperfect substitutes in production (within occupation) with elasticity $\rho > 0$ - see Peri & Sparber (2009) and Burstein, Hanson, Tian & Vogel (2020) among others.[44] Each skilled worker of type i (with I, D) exerts (inelastic) effort and produces A_o^i units of service of occupation o. As in Burstein et al. (2020), firms combine skilled native and immigrant workers to produce units of each occupation Q_o,

[42] The innovation activity increases the stock of knowledge of firms. See Griliches (1979) and Romer (1990) for standard model of knowledge stock accumulation.

[43] We do not need to make explicit assumption on the functional form aggregating the two service occupations in production. The reader can easily imagine a Cobb-Douglas aggregator and our conclusions hold.

[44] We make the simplifying assumption that low-skilled workers are not involved in the innovation process of the firm. Considered the focus of the paper, this assumption is highly plausible.

according to a CES aggregation:

$$Q_o = \left[\left(A_o^I L_o^I \right)^{\frac{\rho-1}{\rho}} + \left(A_o^D L_o^D \right)^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}} \quad \text{for } o = T, M. \tag{4}$$

Hence, the overall efficiency of the innovation (patenting) activity of firms depends on the efficiency (i.e. output per worker) of each service occupation o. The output per worker in each occupation can be expressed as:

$$\frac{Q_o}{L_o^I + L_o^D} = \left[\left(A_o^I sh_o \right)^{\frac{\rho-1}{\rho}} + \left(A_o^D (1 - sh_o) \right)^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}} \quad \text{for } o = T, M. \tag{5}$$

where sh_o indicates the share of skilled immigrant workers employed by the firm in occupation o. In a frictionless local labor market, the efficiency of each service occupation in eq. (5) – and therefore the efficiency of the overall patenting activity – is maximized when the immigrant-native ratio L_o^I/L_o^D is equal to:[45]

$$\frac{L_o^I}{L_o^D} = \left[\frac{A_o^I}{A_o^D} \right]^{\rho-1} \quad \text{for } o = T, M. \tag{7}$$

If immigrant and native workers are equally productive, then 1 is the optimal immigrant-to-native ratio in the production of a given occupation o. More generally, the higher the ratio of productivity between immigrant and native workers employed in occupation o, the higher the optimal immigrant-to-native ratio in o. It is the structure of comparative advantage of immigrant *vs* native workers in, respectively, managerial and technical tasks that shapes the optimal allocation of immigrant and native workers across occupations:

$$\frac{L_o^I/L_o^D}{L_{o'}^I/L_{o'}^D} = \left[\frac{A_o^I/A_o^D}{A_{o'}^I/A_{o'}^D} \right]^{\rho-1} \tag{8}$$

If immigrant workers have a comparative advantage in occupation o rather than in o', the right side of equation (8) will be larger then one ($A_o^I/A_o^D > A_{o'}^I/A_{o'}^D$), and the optimal immigrant-to-native ratio in occupation o will be larger than in o'.

[45] See appendix section D for more details on the derivation. Notice that the efficiency condition of each occupation service can be expressed in terms of the share of immigrants (over total employment):

$$sh_o = \frac{\left[A_o^I/A_o^D \right]^{\rho-1}}{1 + \left[A_o^I/A_o^D \right]^{\rho-1}} \quad \text{for } o = T, M. \tag{6}$$

Proposition 1 *Firms employ relatively more intensively immigrant workers in occupation where they have comparative advantage with respect to native workers, i.e.* $L^I_o/L^D_o > L^I_{o'}/L^D_{o'}$ *if* $A^I_o/A^D_o > A^I_{o'}/a^D_{o'}$.

If immigrants are relatively more productive than natives in technical tasks (i.e. $A^I_T/A^D_T > A^I_M/A^D_M$) then the immigrant-to-native ratio will be larger in technical than in managerial tasks. This is plausibly the case if managerial tasks need communication proficiency and immigrants lacks language skills with respect to native workers. In the limit case in which immigrants have extremely poor language skills at destination (or are *de facto* excluded by managerial occupations), $A^I_M \simeq 0$ and the immigrant-to-native optimal ratio in managerial occupation is close to zero (i.e. only native workers in managerial tasks).

The consequences of a skilled immigrant labor supply shock on the patenting activity of firms can be outlined by comparing the allocation of tasks in pre- *vs* post-migration shock. In the *ex-ante* situation (pre-migration shock) all firms employ a sub-optimal immigrant-to-native ratio in technical and/or managerial occupations because of a lack in high-skilled immigrant labor supply. In the post-migration period, when a sufficient number of skilled immigrants are available in the local labor market, firms can re-allocate immigrant and native workers across occupation (i.e. L^I_o/L^D_o) according to their comparative advantage. In the more realistic case in which the lack of communication skills among immigrant workers makes them less productive than natives in managerial tasks (and conversely relatively more productive in purely technical tasks), the larger availability of skilled immigrant workers in the local labor market will allow firms to move from a sub-optimal to an optimal immigrant-to-native ratio in technical tasks, re-allocate tertiary educated native workers in managerial positions and improve the overall efficiency in both technical and managerial tasks.[46]

Proposition 2 *The increase in the labor supply of skilled immigrant workers allows firm to move from a sub-optimal to an optimal immigrant-to-native allocation in both managerial and technical tasks. This improves the overall efficiency of the innovation process in the firm and hence the number of patents.*

In what follows we benefit from the detailed information on the occupation covered by immigrant and native workers in each French firm to test the mechanism outlined above.

[46] In the limit case of $A^I_M \simeq 0$ in which it is optimal having only native workers in managerial occupations, the patenting activity of firms can still benefit from immigration by improving the efficiency of the purely technical tasks.

7.2 Immigration, tasks allocation and patenting activity: results

To empirically test the task allocation mechanism discussed in the previous section we proceed in three steps. First, we test whether the presence of skilled immigrants in the district pushes firms to re-allocate workers across tasks (in this case the dependent variable is the number of workers that switch occupation within the same firm in a given district-year) - see table 10. Second, we test whether the larger availability of tertiary educated immigrants in the district increases the firm's immigrant-to-native ratio in technical tasks more than in managerial tasks (here approximated by PCS occupation codes 47 and 38) - see table 11. Finally, to close the loop, we propose a 2SLS approach in which the imputed share of skilled migrant workers (shift-share IV) is used to instrument the firm's relative immigrant-to-native ratio in technical and managerial tasks, and this to explain the patenting activity of firms - see table 12.

Table 10 shows the positive effect of skilled migration shock on the within-firm switches for native (columns 1) and immigrant workers (column 2). This preliminary evidence suggests that a larger availability of skilled immigrant workers in the local labor market pushes French firms to re-allocate both immigrant and native workers across occupations. In line with the theoretical intuition discussed above, native workers show larger elasticity in switching occupation than immigrants (compare column 1 and 2 in table 10) as they are expected to be re-allocated from technical to managerial tasks. Interestingly, the migration induced re-allocation of tasks ends up in an increase share of immigrants employed in purely technical skills - see table E1.[47]

In line with the theoretical mechanism discussed above, the migration-induced re-allocation of tasks within the firm should come with an increase in the migrant-to-native ratio in both managerial and techies occupation.[48] Accordingly, table 11 shows that an increase in the share of skilled immigrants in the district pushes French firms to increase the immigrant-to-native ratio in both managerial and technical tasks (see columns 1 and 2), and the more so in technical occupations (see columns 3-5). This is exactly what our simple theoretical framework predicts.[49] Finally, in table 12 we show that the

[47] Our argument bases on the efficiency gain in the innovation process due to the (re)allocation of communication *vs* technical tasks among native and immigrant workers. However, the inflow of skilled immigrants in the local labor market may simply reflect a general increase in the size of workforce (native *plus* immigrant) dedicated to the innovation process (scale effect). Table C3 in appendix shows that while a positive immigrant labor supply shock increases the number of immigrants employed in the firm in technical occupations, it does not affect the number of natives in skilled/techies occupations. This testifies the absence of a general increase in the size of the workforce (involving also native workers) dedicated to the firm's innovation activity, i.e. absence of scale effect.

[48] The immigrant-to-native ratio in the managerial tasks should remain unchanged and close to zero only in the limit case in which $A_M^I \simeq 0$.

[49] In table E2 we dig more in the re-allocation of native workers across occupations, and show that in presence of an

increase in the immigrant-to-native ratio in technical vs. managerial tasks (first stage), instrumented with the exogenous change in the share of tertiary educated immigrants (shift-share IV), positively affects the overall patenting activity of the firm (second stage). The first stage coefficients reported at the bottom of table 12 support the task re-allocation channel discussed above (i.e. immigrant shocks pushing firms to allocate immigrant workers relatively more in technical tasks). The second stage results confirm that an improved allocation of tasks across immigrant and native workers implies a boost in the patenting activity of firms.[50]

The mechanism discussed so far is based on the implicit assumption that skilled immigrant workers have a *comparative* advantage in technical tasks, while skilled native workers have a *comparative* advantage in language intensive tasks (such as directing, training or organizing people). This assumption is less plausible for francophone skilled immigrants, whose language skills are comparable to natives. However, it must be noted that in the French system, high managerial positions (*cadres d'entreprises*) are *de jure* or *de facto* reserved to native workers graduated in *Grands Écoles*. To further reduce such a concern, in tables 11 and 12 we show a robustness check using non-francophone immigrant origins to build our IV. By doing so, the variation in the instrumented share of skilled immigrants does not reflect the variation of immigrants from francophone origins, who may have a comparative advantage in language intensive tasks.[51] Results reported in the last columns of tables 11 and 12 show the robustness of our baseline results to this check.

– Tables 10, 11 and 12 about here –

7.3 Alternative mechanisms: Knowledge diffusion and quality of migrants

The task allocation mechanism is one possible explanation for the innovation-enhancing effect of skilled immigration. We now consider two alternative channels – the diffusion of knowledge conveyed by

increased share of skilled immigrants in the district native workers are re-allocated toward managerial positions (and away from production-related tasks), see panel a columns 1-2 and 5-6 of table E2. Panel b of table E2 shows that native workers are re-allocated towards language and communication intensive managerial positions such as Sales Executives (see columns 1-2 of panel b in table E2).

[50] The tasks reallocation mechanism can be also showed by using the relative allocation of immigrant and native workers in technical *vs* managerial tasks, as in Peri & Sparber (2009). As a robustness check we follow this approach in tables E3 and E4 and our results hold. Table E3 shows the positive effect of an exogenous skilled migration shock (IV estimation) on the managerial-to-technical task allocation of native workers. Table E4 shows the positive effect of skilled immigration on the managerial-to-technical task allocation of native workers (first stage), and the effect of this on the patenting activity of firms (second stage).

[51] Ideally, we should have used the share of non-francophone skilled immigrants as main (endogenous) explanatory variable. However, we do not have information on the country of origin of immigrants in each district from DADS data. So, we rely on the non-francophone inflows of immigrants in France (OECD, IMD data) to build our IV and exclude the variation from francophone origin from our IV.

immigrants at destination (Bahar et al. 2020); and the the average quality of skilled immigrants at destination – and check the robustness of our results to controlling for them. Bahar et al. (2020) show that countries receiving immigrant inventors from origins specialized in patenting in specific technology are more likely to increase their patenting applications in that same technology. In columns (3)-(6) of table 12 we therefore test the validity of the task-allocation channel *net* of the knowledge diffusion and quality of immigrants channels. To approximate the diffusion of knowledge that immigrants provide at destination (KD_{dt}), we calculate the weighted average number of patents "transferred" into French districts by origin-specific migrant groups:

$$\text{KD}_{dt} = \sum_{o} \left[\left(\frac{M_{d,o,1980}}{\sum_d M_{d,o,1980}} \right) \times Patents_{ot} \right] \tag{9}$$

where the number of patents delivered by each macro-origin o at time t, $Patents_{ot}$,[52] is allocated across districts based on the geographical distribution of migrants in 1980.[53] This variable captures the patenting intensity of the origin composition of immigrants in each French district: higher values of KD_{dt} suggests that the district hosts a larger share of immigrants originating by patenting intensive countries. Results in columns (3)-(6) of table 12 show a positive and significant effect of the knowledge diffusion channel on the patenting activity of firms in line with Bahar et al. (2020). Importantly, the task-allocation channel remains statistically significant.

Since immigrants are positively selected at origin, the positive migration-innovation nexus may be simply driven by the average quality (and quality dispersion) of high-skilled immigrant workers in French districts. To precisely control for this channel, in columns (3)-(6) of table 12 we control for the average quality of immigrant workers in each French district, and its dispersion. We approximate the quality of workers in our sample by their residual wage. Namely, we estimate a mincerian (log) wage regression having the age, the age squared, the gender of the workers, district and sector-year dummies as covariates. The residual term of this estimation can be considered a coarse (but intuitive) proxy for the innate quality of each worker. We then calculate the average and inter-quartile range of immigrant workers' residual wage in each district-year and include as a control in table 12. In line with intuition, the average quality of immigrant workers is positively correlated with the patenting activity of firms,

[52]As discussed in the Data section, we do not have information on the specific country of origin of immigrants, but only on five macro-region of origin – see Table A4. So, to build the variable $Patents_{ot}$ we computed the average number of patents delivered by countries in each macro-region of origin o at time t.

[53]We use the geographical distribution of immigrants in 1980, as for the construction of the shift-share IV, to reduce the endogeneity of the weights used to allocate origin-specific patents across local labor markets.

although imprecisely estimated. More importantly, our coefficient of interest, i.e. the immigrant-to-native ratio in technical vs. managerial tasks remains positive and statistically significant. This suggests the validity of the task-allocation channel *conditional* on the two other possible mechanisms at play.

7.4 The composition of patenting teams

So far we made the implicit assumption that the within-firm reallocation of skilled native and migrant workers towards respectively communication and technical tasks isomorphically translates into a more efficient native-migrant inventors mix in the patenting teams of the firm. In this section, we benefit from Patstat data on the specific composition of the patenting teams for a sub-sample of French firms,[54] and directly test whether a positive shock in the skilled migrant labor supply makes French firms use relatively more intensively migrant inventors in patenting teams (as predicted by our simple model).

In table 13 we show that an increase in the (instrumented) share of skilled immigrant workers in the district positively affects the share of migrant inventors of a French firm – see columns (1)-(5). In columns (6)-(7) we get closer to our theoretical framework and test the effect of changes in the share of skilled immigrants in the district on the relative migrant-to-native ratio in inventors over managerial occupations. In line with our mechanism (and theoretical model), a positive change in the share of skilled immigrant workers in the district makes firms allocate relatively more immigrants to innovation than communication-intensive tasks. The change in the migrant-native composition of patenting teams is further suggestive evidence of our mechanism at play.

8 Conclusions

In this paper we have explored the impact of skilled migration to a European country, in particular in terms of innovation. Our results show that France has received non trivial numbers of skilled migrants in recent years and, because of that, has experienced an increase in the number of patents. We find that the innovation effect of skilled immigrants is not just a scale effect, with respect to the total number of skilled workers. Indeed the positive impact on patenting activity is larger for immigrant relative to French skilled workers. We explain this result on the basis of a task specialization story

[54] Patstat data does not cover the entire sample of patents filed by French firms in the period 1995-2020. For this reason, we consider this last set of results as just a check of the mechanism.

according to which French skilled workers specialize in managerial, administrative tasks while foreign skilled workers specialize in technical, research tasks. Gains from the specialization of each group of workers in their comparative advantage task lead to increases in innovation. Importantly, our results on the task specialization channel are robust to controlling for other mechanisms of impact for which there is evidence in the literature (Bahar et al. 2020).

Since our paper focuses on France, an important question relates to the external validity of our results. While only careful empirical analysis can provide a definitive answer, recent evidence suggests that our findings might extend to other destination countries in Europe. A recent report by the World Bank on skilled migration to Europe shows that "the number of high-skilled migrants in the EU, defined as migrants with some tertiary education, more than tripled over the period 2004–18, increasing from about 4 million to 13 million" (World Bank 2022, page 19). In addition, the same report shows that the occupation composition of skilled migrants to Europe is quite different from that of skilled natives. Just like in the case of France, skilled migrants to European countries are more likely to have jobs requiring technical and quantitative skills (for example, information and communication technology (ICT) software developers, engineers, and medical doctors) while skilled natives tend to be in communication-intensive occupations (such as, sales, legal and finance professionals, teachers, and administrative workers). This evidence suggests that France might not be an isolated case, within Europe, in terms of the innovation-migration nexus and of the task specialization channel.

In general, more research is needed on the economic impact of skilled migration to Europe. This is especially important because skilled migration is not only likely to be beneficial in economic terms, it appears to be politically feasible too. Public opinion is by and large in favor of skilled migration. For example, a recent survey of 12 (mostly European) countries by the Pew Research Center shows that, in 2018, in all but two of them (Italy and Israel), more than half of those interviewed – who are representative of the entire population – would encourage high-skilled individuals to immigrate and work in their countries (Connor & Ruiz 2019)[55]. In particular, in France, 68% of the sample is supportive of skilled migration, against 31% opposed to it. To conclude, skilled migration represents an opportunity for policymakers in Europe to make progress in liberalizing labor markets, at the same time avoiding a political backlash.

[55] The full list of countries covered by the survey includes: Sweden, UK, Canada, Germany, Australia, U.S France, Spain, Netherlands, Greece, Israel and Italy

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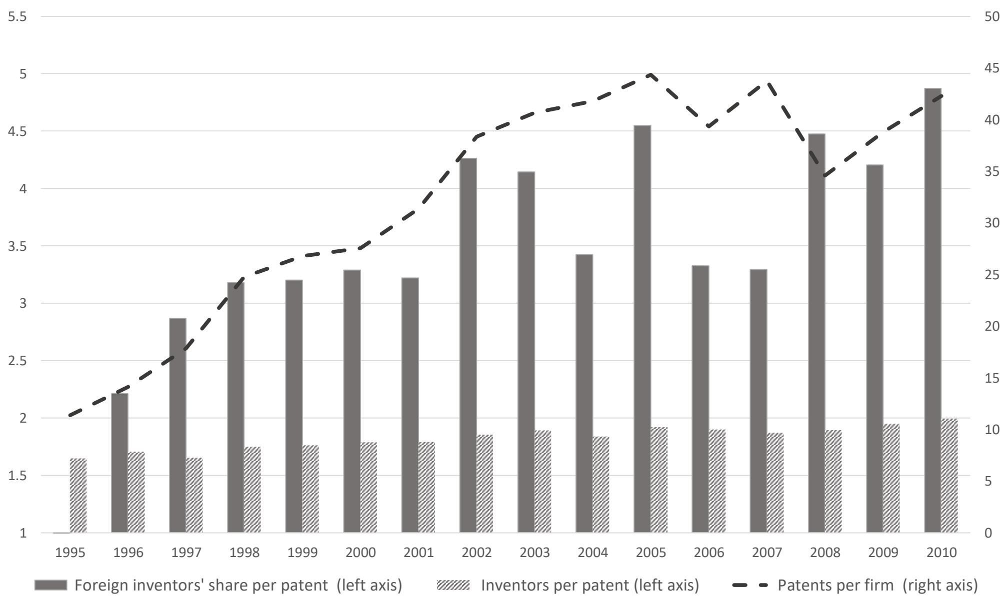
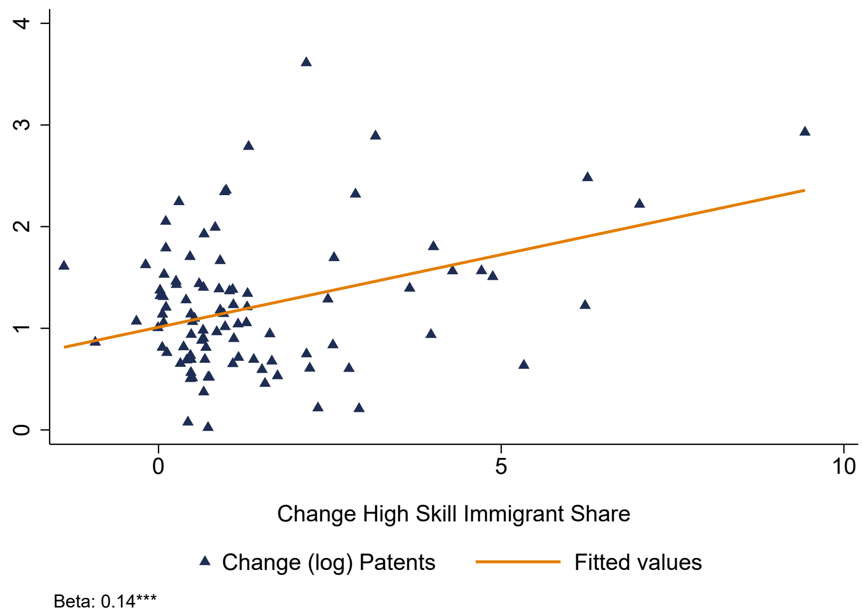
9 Figures and tables

Figure 1: Trend in the average size of innovation teams (number of inventors per patent), number of foreign inventors per patent, and patents per firm in France.



Source: Authors calculations DADS and ORBIS data. Weighted Averages across French firms using firm's value added shares as weights.

Figure 2: Correlation between the change in log patents (y axis) and the change in the share of skilled immigrant workers (x axis) across French districts (1995-2010)



Source: Authors calculations on Orbis and DADS data.

Table 1: In-sample descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
		District level variable			
Number of patents	1,504	308.1	867.7	0	10538
Number of patents (ln)	1,504	5.4	1.4	0	10
Share Skilled Natives	1,504	31.2	10.1	18.3	76
Share Skilled Migrants	1,504	1.9	2.3	0	24.5
VA per firm (ln)	1,504	14	1.1	10.4	17.8
KL ratio (ln)	1,504	0.3	0.2	-0.7	1.1
Total VA in district (ln)	1,504	6.5	0.6	4.7	9.4
Workforce	1,504	27048	19809	792	152355
		Firm level variable			
Number of patents	51,704	8.0	53.9	0.0	4775
Number of patents (ln)	51,704	1.5	1.3	0.0	9.2
Share Skilled Natives	51,704	35.6	13.2	18.3	76
Share Skilled Migrants	51,704	2.7	3	0.0	24.5
VA per worker (ln)	51,704	4.3	0.7	-2.7	13
KL ratio (ln)	51,704	-0.3	0.9	-7.3	8.5
Total VA in the firm (ln)	51,704	8.1	1.7	-2.7	15.6

Source: Authors' calculation on DADS and FICUS/FARE data.

Table 2: Share of high skilled natives and migrants (observed and imputed) across districts.

Dep var:	Share Skilled Migrants					
	Observed			*Imputed*		
	(1)	(2)	(3)	(4)	(5)	(6)
Sh Skilled Nat	-0.246***	-0.395***	-0.059	-0.003	-0.000	-0.014
	(0.080)	(0.097)	(0.057)	(0.003)	(0.000)	(0.017)
Specification	Level	First Diff	Long Diff	Level	First Diff	Long Diff
District Fixed Effects	Yes	No	No	Yes	No	No
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,504	1,410	94	1,504	1,410	94
R-squared	0.734	0.474	0.312	0.909	0.318	0.441

Note: Dependent variable is the share of skilled immigrants in level, first and long (1995-2011) difference (observed and imputed). ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels respectively.

Table 3: Pre-trend test for IV validity.

Dep var:	Δ patents in each district:			
	1990-1970	*1980-1960*	*1970-1950*	*1960-1940*
	(1)	(2)	(3)	(4)
$\Delta\ IV_{2010-1995}$	0.073	0.084	0.038	0.092
	(0.100)	(0.098)	(0.215)	(0.236)
Observations	93	93	93	93
R-squared	0.188	0.237	0.210	0.290
Fixed Effects	Region	Region	Region	Region
Main Origins:				
$\Delta\ IV^{OtherOrigins}_{2010-1995}$	0.069	0.075	0.029	0.087
	(0.096)	(0.092)	(0.204)	(0.228)
$\Delta\ IV^{Africa}_{2010-1995}$	7.140	9.888	3.076	-3.481
	(4.900)	(5.993)	(8.096)	(7.254)
$\Delta\ IV^{EEC\&Centr.Asia}_{2010-1995}$	6.386	39.307	32.870	20.201
	(22.961)	(27.540)	(41.383)	(43.974)
$\Delta\ IV^{Asia}_{2010-1995}$	-2.561	-0.560	7.341**	4.881
	(3.384)	(2.426)	(2.823)	(3.271)
$\Delta\ IV^{Europe}_{2010-1995}$	-3.985	-2.621	1.740	-2.461
	(3.668)	(3.681)	(7.601)	(9.779)
Observations	93	93	93	93
Fixed Effects	Region	Region	Region	Region

Note: Dependent variable is the log difference in the number of patents in the district over different sub-periods. ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels respectively.

Table 4: Patents and high skilled immigrants in the district. OLS and 2SLS estimations with region fixed effects.

Dep var:	# Active patents in the district (ln)			
	(1)	(2)	(3)	(4)
High Skill Migrants (sh)	0.107***	0.165***		
	(0.020)	(0.059)		
High Skill Natives (sh)	0.077***	0.082***		
	(0.010)	(0.013)		
Techies Migrant (sh)			0.113***	0.856***
			(0.029)	(0.261)
Techies Natives (sh)			0.099***	0.082**
			(0.015)	(0.037)
$\mathbf{X}_{dt}$	Yes	Yes	Yes	Yes
Estimator	OLS	2SLS	OLS	2SLS
Region Fixed Effects	Yes	Yes	Yes	Yes
District Fixed Effects	No	No	No	No
Year Fixed Effects	Yes	Yes	Yes	Yes
IV: High Skill Migrant (sh)	no	yes	no	yes
IV: High Skill Natives (sh)	no	yes	no	yes
Observations	1,504	1,504	1,504	1,504
Cluster	dep	dep	dep	dep
F-test first stage		15.64		4.728
Coeff first stage Mig sh		1.552***		0.559*
Coeff first stage Nat sh		4.926***		3.172***
F-test (H0: equal coeff)		0.119		0.002

Note: Dependent variable is the log of the number of active patents in the districts. Standard errors adjusted for clustering by district. ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels respectively.

Table 5: Patents and high skilled migrants in the district. OLS, 2SLS and IV PPML estimations with district fixed effects.

Dep var:	# Active patents in the district (ln)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
High Skill Mig. (sh)	0.026*	0.115***	0.119***	0.124***	0.126***	0.108***	0.080**	0.119***	0.153***
	(0.016)	(0.023)	(0.026)	(0.026)	(0.028)	(0.026)	(0.032)	(0.0270)	(0.031)
High Skill Nat. (sh)	0.013		0.036**						
	(0.012)		(0.016)						
VA per firm (ln)				-0.218	-0.590	-0.253	-0.316	-0.446	-0.152
				(0.408)	(0.536)	(0.393)	(0.383)	(0.394)	(0.443)
Capital/VA				0.124	0.164	0.125	0.127	0.147	0.123
				(0.125)	(0.153)	(0.122)	(0.118)	(0.131)	(0.133)
Tot VA (ln)				-0.165	0.076	-0.070	0.098	0.0546	-0.340
				(0.494)	(0.620)	(0.479)	(0.490)	(0.455)	(0.501)
Estimator	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	IV PPML	2SLS
Region Fixed Effects	No	No	No	No	No	No	No	No	No
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IV: High Skill Mig. (sh)	no	yes	yes	yes	yes	yes	yes	yes	yes
IV: High Skill Nat. (sh)	no	no	no	no	no	no	no	no	no
Base year IV	1980	1980	1980	1980	1980	1990	1975	1980	1980 Alternative shift IV
Sample period	95-10	95-10	95-10	95-10	95-08	95-10	95-10	95-10	95-10
Observations	1,504	1,504	1,504	1,504	1,316	1,504	1,504	1,504	1,504
Cluster	dep	dep	dep	dep	dep	dep	dep	dep	dep
F-test first stage		14.66	11.36	14.95	8.507	15.27	18.57		7.32
Coeff first stage Mig sh		2.589***	2.528***	2.612***	3.029***	1.612***	2.324***	2.612***	6.795***

Note: Dependent variable is the log of the number of active patents in the districts. Standard errors adjusted for clustering by district. ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels respectively.

Table 6: Patents and high skilled migrants in the district. Robustness checks.

Dep var:	# Pat. (ln)	# Pat. per worker	Δ Pat. per 100,000 people	# Pat. (ln)	# Pat. (ln)	Δ Pat.	Δ Pat.	# Pat. (ln)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Techies Mig. (sh)	0.211***							
	(0.072)							
High Skill Mig. (sh)		0.019***	0.887***					0.124***
		(0.005)	(0.359)					(0.026)
High Skill Mig / Tot Skilled				0.114***				
				(0.029)				
High Skill Impu. Mig (sh)					0.335***			
					(0.081)			
Δ High Skill Mig. (sh)						0.268***	0.204***	
						(0.074)	(0.062)	
Estimator	2SLS	2SLS	2SLS	2SLS	OLS	2SLS	2SLS	2SLS
Specification	Baseline	Baseline	First Diff.	Baseline	Red. Form	First Diff.	Long Diff.	IV no Franco.
$\mathbf{X}_{dt}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	No	No	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes
Sample period	95-10	95-10	95-10	95-10	95-10	95-10	95-10	95-10
Observations	1,504	1.504	1.410	1.504	1.504	1.410	94	1,054
Cluster	dep	dep	dep	dep	dep	dep	dep	dep
F-test first stage	6.239	14.95	15.62	7.952	-	25.99	36.48	14.35
Coeff first stage Mig sh	1.588***	2.612***	2.708***	1.649***	-	1.535***	2.197***	2.414***

Note: Standard errors adjusted for clustering by district. ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels respectively.

Table 7: High skilled migrants and firms' patenting activity. OLS and 2SLS with firm fixed effects.

Dep var:	# Active patents in the firm (ln)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
High Skill Mig. (sh)	0.012***	0.047***	0.052***	0.061***	0.052***	0.053***			0.064***	
	(0.004)	(0.013)	(0.013)	(0.016)	(0.013)	(0.013)			(0.018)	
Techies Mig. (sh)							0.092***	0.096***		0.111***
							(0.023)	(0.027)		(0.031)
VA per worker (ln)			-0.016**	-0.012	-0.016**	-0.016**	-0.016**	-0.012	-0.016**	-0.016*
			(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Capital/VA (ln)			0.079***	0.059***	0.079***	0.079***	0.081***	0.060***	0.082***	0.084***
			(0.014)	(0.015)	(0.014)	(0.014)	(0.014)	(0.015)	(0.014)	(0.014)
VA (ln)			0.107***	0.074***	0.107***	0.107***	0.108***	0.075***	0.109***	0.110***
			(0.017)	(0.018)	(0.017)	(0.017)	(0.017)	(0.019)	(0.016)	(0.016)
Estimator	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Firm-District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IV: High Skill Mig. (sh)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Base year IV		1980	1980	1980	1990	1975	1980	1980	Alternative shift IV	
Sample period	95-10	95-10	95-10	95-08	95-10	95-10	95-10	95-08	95-10	95-10
Observations	51,704	51,704	51,704	43,754	51,704	51,704	51,704	43,754	51,704	51,704
Cluster	id rt	id rt	id rt	id rt	id rt	id rt	id rt	id rt	id rt	id rt
F-stat first stage		258.6	257.5	82.04	271.8	216.5	111.5	71.90	62.97	57.74
Coeff first stage		2.154***	2.150***	2.339***	1.329***	1.910***	1.217***	1.484***	5.755***	3.294***

Note: Dependent variable is the log of the number of active patents in the firm. Standard errors adjusted for clustering by firm and region-year. ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels respectively.

Table 8: High skilled migrants and firms' patenting activity by type of firm. OLS and 2SLS with firm fixed effects.

Dep var:	# Active patents in the firm (ln)					
	(1)	(2)	(3)	(4)	(5)	(6)
High Skill Mig. (sh)	0.007	0.011**	-0.027**	0.029**	0.045***	-0.013
	(0.005)	(0.005)	(0.010)	(0.012)	(0.013)	(0.031)
High Skill Mig. (sh) × High Prod	0.018***			0.052***		
	(0.007)			(0.016)		
High Skill Mig. (sh) × High K/L		0.011*			0.031*	
		(0.007)			(0.016)	
High Skill Mig. (sh) × Big Firm			0.041***			0.067**
			(0.011)			(0.030)
Estimator	OLS	OLS	OLS	2SLS	2SLS	2SLS
$\mathbf{X}_{it}$	Yes	Yes	Yes	Yes	Yes	Yes
Firm-District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Sector-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
IV: High Skill Migrant (sh)	No	No	No	Yes	Yes	Yes
Base year IV				1980	1980	1980
Observations	51,704	51,704	51,704	51,704	51,704	51,704
Cluster	id rt	id rt	id rt	id rt	id rt	id rt
F-stat first stage				120.6	128.2	130
Coeff first stage Mig sh				2.206***	2.157***	1.886***
Coeff first stage Interaction				2.923***	3.029***	2.927***

Note: Dependent variable is the log of the number of active patents in the firm. High productive, high capital intensive and big firms are those above the 75^{th} percentile of labor productivity, capital intensity and size distribution. Control variables $\mathbf{X}_{it}$ included but not reported. Standard errors adjusted for clustering by firm and region-year. ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels respectively.

Table 9: High skilled migrants and firms' patenting activity. Robustness checks.

Dep var:	# Patents (ln)	# Patents (ln)	# Patents (ln)
	(1)	(2)	(3)
High Skill Mig. in the firm (sh)	0.149***		
	(0.058)		
High Skill Mig. (sh)		0.066***	0.052***
		(0.014)	(0.013)
High Skill Mig. (sh) x Big City		-0.020	
		(0.016)	
Estimator	2SLS	2SLS	2SLS
IV	Baseline	Baseline	No Franco. Mig
$\mathbf{X}_{it}$	Yes	Yes	Yes
Firm-District Fixed Effects	Yes	Yes	Yes
Sector-Year Fixed Effects	Yes	Yes	Yes
Sample period	1995-2010	1995-2010	1995-2010
Observations	51,704	51,704	51,704
Cluster	id rt	id rt	id rt
F-test first stage	13.35	59.20	254.3
Coeff first stage Mig sh	0.752***	3.664***	1.983***
Coeff first stage Mig sh x Big City		2.351***	

Note: Dependent variable is the log of the number of active patents in the firm. Control variables $\mathbf{X}_{it}$ included but not reported. Standard errors adjusted for clustering by firm and region-year. ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels respectively.

Table 10: The impact of migrants on the number of within firm worker's occupation switches in each district-year.

Dep var:	# Occupation Switches (ln)	
	Natives	*Migrants*
	(1)	(2)
High Skill Migrants (sh)	0.006***	0.003***
	(0.002)	(0.001)
Estimator	2SLS	2SLS
$\mathbf{X}_{dt}$	Yes	Yes
District Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
IV: High Skill Migrant (sh)	Yes	Yes
Base year IV	1980	1980
Observations	1,504	1,504
Cluster	dep	dep
F-stat first stage	11.75	11.75

Note: Dependent variable is the number of workers in the district that change occupation within the same firm. Control variables in $\mathbf{X}_{dt}$ included but not reported. Standard errors adjusted for clustering by department. ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels respectively.

Table 11: The impact of skilled migrants on the migrant-to-native ratio in managerial (M) and technical (T) occupations.

Dep var:	$ln\left(\frac{L_M^I}{L_M^D}\right)$	$ln\left(\frac{L_T^I}{L_T^D}\right)$	$ln\left(\frac{L_T^I/L_T^D}{L_M^I/L_M^D}\right)$			
	(1)	(2)	(3)	(4)	(5)	(6)
High Skill Migrants (sh)	0.042***	0.070***	0.028***		0.027**	
	(0.014)	(0.016)	(0.011)		(0.011)	
Techies Migrants (sh)				0.049**		0.049**
				(0.020)		(0.020)
Estimator	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
$\mathbf{X}_{it}$	Yes	Yes	Yes	Yes	Yes	Yes
Firm-District FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
IV: High Skill Mig (sh)	Yes	Yes	Yes	Yes	Yes	Yes
Base year IV	1980	1980	1980	1980	1980	1980
					No Franco. Mig	
Observations	51,704	51,704	51,704	51,704	51,704	51,704
Cluster	id rt	id rt	id rt	id rt	id rt	id rt
Coeff first stage	2.150***	2.150***	2.150***	1.217***	1.983***	1.116***
F-test first stage	257.5	257.5	257.5	111.5	254.28	109.73

Note: Dependent variable is the log of the ratio between migrant and native workers in respectively managerial and technical occupations (and the ratio of the two in columns 3-6). Controls variables in $\mathbf{X}_{it}$ always included. Standard errors adjusted for clustering by firm and region-year. ***, **, *, significantly different from 0 at the 1%, 5%, and 10% levels respectively.

Table 12: High skilled migrants and the patenting activity of firms *via* the tasks reallocation channel.

Dep var:	# Active patents in the firm						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$ln\left(\frac{L_T^I/L_T^D}{L_M^I/L_M^D}\right)$	1.361**	1.868**	0.801*	1.789**	0.755*	0.768*	0.768*
	(0.564)	(0.843)	(0.451)	(0.837)	(0.442)	(0.452)	(0.465)
KD			1.015**		0.957**	0.934**	0.934**
			(0.488)		(0.436)	(0.432)	(0.435)
Migrant Quality^{Average}				0.095	0.130	0.018	0.018
				(0.282)	(0.158)	(0.163)	(0.164)
Migrant Quality^{Dispersion}						0.210**	0.210**
						(0.105)	(0.105)
Estimator	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
$\mathbf{X}_{it}$	No	Yes	Yes	Yes	Yes	Yes	Yes
Firm-District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IV: Task comp.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Base year IV	1980	1980	1980	1980	1980	1980	No Franco. Mig
Observations	51,704	51,704	51,704	51,704	51,704	51,704	51,704
Cluster	id rt	id rt	id rt	id rt	id rt	id rt	id rt
Coeff first stage	0.074***	0.060**	0.098**	0.057**	0.096**	0.096**	0.087**
F-test	9.17	5.95	6.02	5.49	5.67	5.70	5.40

Note: Dependent variable is the number of active patents in the firm (ln). Standard errors adjusted for clustering by firm and region-year. ***, **, * significantly different from 0 at the 1%, 5% and 10% levels respectively.

Table 13: High skilled migrants and the composition of patenting teams.

Dep var:	$\left(\frac{L^I_{Inv}}{L^I_{Inv}+L^D_{Inv}}\right)$					$\left(\frac{L^I_{Inv}/L^D_{Inv}}{L^I_M/L^D_M}\right)$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
High Skill Migrants (sh)	0.147	1.818**		1.547*		0.074*	
	(0.377)	(0.874)		(0.898)		(0.042)	
Techies Migrants (sh)			3.265**		2.803*		0.135*
			(1.604)		(1.659)		(0.078)
Estimators	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
$\mathbf{X}_{it}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IV: High Skill Mig (sh)	No	Yes	Yes	Yes	Yes	Yes	Yes
Base Year		1980	1980	1980	1980	1980	1980
Observations	6,967	6,967	6,967	6,967	6,967	7,140	7,140
Cluster	id rt	id rt	id rt	id rt	id rt	id rt	id rt
Coeff. first stage	OLS	1982	1982	1982	1982	1982	1982
F-test first stage		160.3	62.17	154.4	59.61	159.6	61.15

Note: Dependent variable is the number of active patents in the firm (ln). Standard errors adjusted for clustering by firm and region-year. ***, **, * significantly different from 0 at the 1%, 5% and 10% levels respectively.

A Additional figures and tables

Table A1: Number and share of immigrants in France by year.

Year	Tot. Population (in thousands)	N. Immigrants (in thousands)	Share of Immi. (over tot. pop.)
1982	54296	4037	7,4
1990	56652	4166	7,4
1999	60187	4387	7,3
2006	63186	5136	8,1
2010	64613	5514	8,5
2011	64933	5605	8,6

Source: French Census data (INSEE)

Table A2: Occupation-education correspondence.

ISCO 1-digit occupation	Education level
Legislators, senior officials and managers	high skilled white collar
Professionals	high skilled white collar
Technicians and associate professionals	high skilled white collar
Clerks	low skilled white collar
Service workers and shop and market sales workers	low skilled white collar
Skilled agricultural and fishery workers	high skilled blue collar
Craft and related trades workers	high skilled blue collar
Plant and machine operators and assemblers	low skilled blue collar
Elementary occupations	low skilled blue collar

Notes: Occupation-education conversion by Eurofond is available here: `https://www.eurofound.europa.eu/surveys/ewcs/2005/classification`

Table A3: District-specific shocks in skilled migrant labor supply and firm's hiring of skilled immigrants.

Dep Var:	Ln(immi_{it})		Dummy ($\text{immi}_{it} > \text{immi}_{i,t-1}$)	
	Panel a: Skilled Immigrants in the firm			
High Skill Migrants (sh)	0.021***	0.062***	0.002	0.007*
	(0.006)	(0.014)	(0.001)	(0.004)
	Panel b: Techies Immigrants in the firm			
High Skill Migrants (sh)	0.020***	0.060***	0.003**	0.011***
	(0.005)	(0.014)	(0.001)	(0.004)
Estimator	OLS	2SLS	OLS	2SLS
$\mathbf{X}_{it}$	Yes	Yes	Yes	Yes
Firm-District FE	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes
IV: High Skill Mig (sh)	No	Yes	No	Yes
Base year IV		1980		1980
Observations	48,816	48,816	46,771	46,771
Cluster	id rt	id rt	id rt	id rt
F-test first stage		238.8		243.8

Note: Dependent variable in columns 1 and 2 is the number of skilled immigrant in the firms. Dependent variable in columns 3 and 4 is a dummy equal to one for positive change in the number of skilled immigrants in the firm. Immigrants' skills are approximated by skilled occupations in panel a, and techies occupation in panel b. ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels respectively.

Table A4: Composition of the immigrants' groups of origins.

Africa	*EEC & Centr. Asia*	*Asia*	*Europe*	*Other Origins*
DZA	BGR	ARM	DEU	CAN
CMR	HUN	KHM	AUT	USA
CAF	POL	CHN	BEL	HTI
COG	ROU	IND	DNK	MEX
CIV	CZE	IRN	ESP	ARG
BEN	SRB(YUG)	ISR	FIN	BRA
GAB	EST	JPN	GRC	CHL
GNQ	LVA	LBY	IRL	COL
MDG	LTU	LBN	ITA	VEN
MLI		SYR	LUX	RUS
MAR		TUR	NOR	AUS
NER		VNM	NLD	
EGY		IRQ	PRT	
SEN		PAK	GBR	
TCD			SWE	
TGO			CHE	
TUN			AND	
MDG				
SOM				
NGA				
ZAR				

Note: Composition of the immigrants origins. *EEC* stands for Eastern European Countries.

Table A5: Pre-trend test in levels.

Dep var:	Δ patents across districts:			
	1990-1970	*1980-1960*	*1970-1950*	*1960-1940*
	(1)	(2)	(3)	(4)
IV_{1995}	0.240	0.300	0.049	0.139
	(0.262)	(0.311)	(0.576)	(0.593)
Observations	93	93	93	93
R-squared	0.189	0.238	0.209	0.288
Fixed Effects	Region	Region	Region	Region
Main Origins:				
$\Delta\ IV^{OtherOrigins}_{2010-1995}$	0.729	0.623	-0.224	0.381
	(0.890)	(0.820)	(1.774)	(2.019)
$\Delta\ IV^{Africa}_{2010-1995}$	1.813*	1.659	-1.219	-1.734
	(0.929)	(1.426)	(1.845)	(1.370)
$\Delta\ IV^{EEC\&Centr.Asia}_{2010-1995}$	1.801	2.235	-1.926	-1.329
	(2.228	(2.410)	(3.843)	(3.867)
$\Delta\ IV^{Asia}_{2010-1995}$	0.532	1.056	-0.364	-0.244
	(1.313)	(1.224)	(1.925)	(1.835)
$\Delta\ IV^{Europe}_{2010-1995}$	0.896	1.549	2.384	3.139
	(1.339)	(1.825)	(2.927)	(3.140)
Observations	93	93	93	93
Fixed Effects	Region	Region	Region	Region

Note: Dependent variable is the log difference in the number of patents in the district over different sub-periods. ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels respectively.

Table A6: Immigrant share and innovation activity with plausibly exogenous instrument.

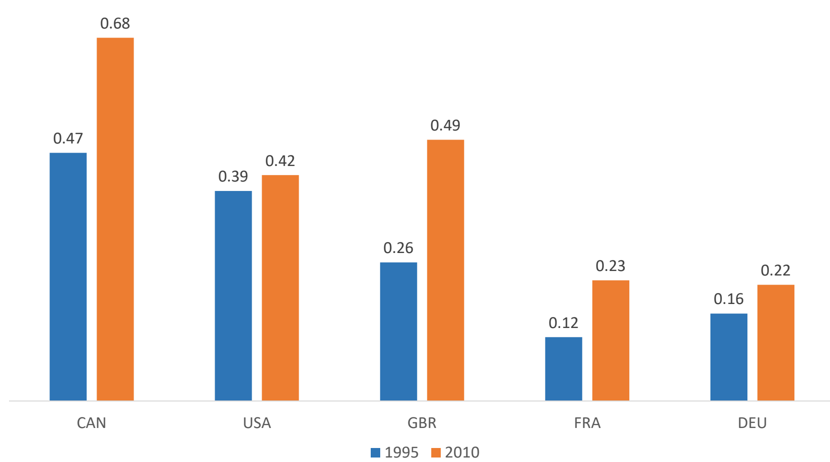
	Union of Confidence Interval estimations		
Dep Var	γ	Min 95% CI	Max 95% CI
Patents in the district (ln)	-0.742	0.070	0.576
	(0.972)		
Patents in the firm (ln)	0.026	0.032	0.273
	(0.502)		

Note: UCI based on γ coefficients from a regression of patents (in log) on the IVs. Clustered standard errors in parenthesis. The number of department for which the instrument is not working is 14 (out of 94). Due to the high number of fixed effects, the boundaries for the firm level specification are obtained on demeaned data.

Table A7: Fixed effects explained variance (R^2).

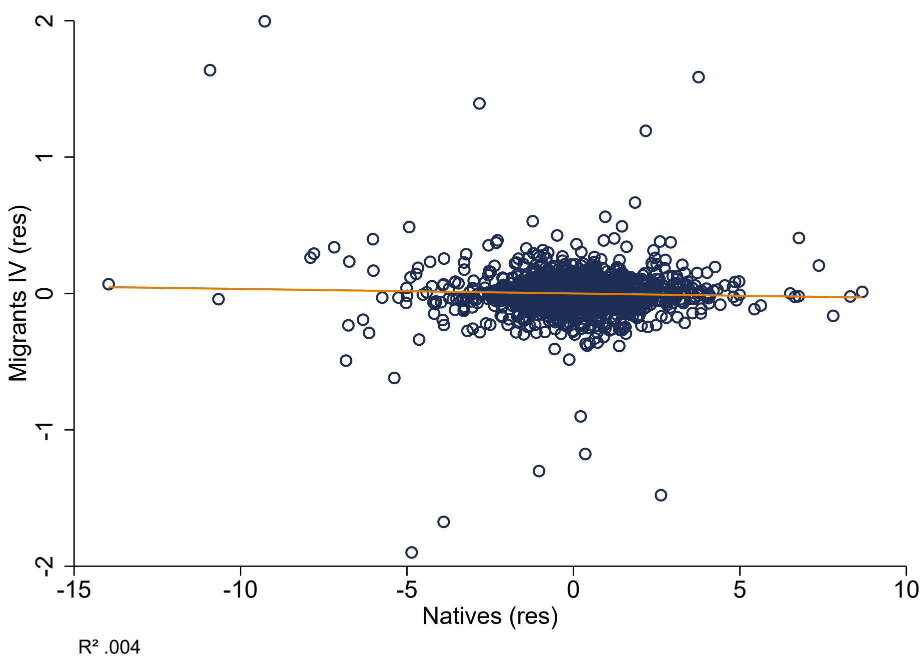
Dep Var:	Included Fixed Effects		
	Region	District	District & Year
Observed Native High Skill (Share)	0.601	0.950	0.964
Imputed Native High Skill (Share)	0.499	0.989	0.991
Imputed Native High Skill (Level)	0.456	0.999	0.999
Imputed Native (Level)	0.598	0.999	0.999
Imputed Migrants (Level)	0.442	0.900	0.915

Figure A1: Share of tertiary educated immigrants (over the total population of foreign-born residents) in France and a selection of developed countries. Comparison of years 1995 and 2010.



Source: Authors calculations on IADB data.

Figure A2: Correlation between high skilled natives and the IV of high skilled migrants. Both variables conditioned on district and year fixed effect.



Source: Authors calculations DADS data.

B District level evidence: robustness checks.

In this section we run a battery of checks showing the robustness of our baseline (district-level) results. We show results based on: (i) alternative definition of workers' skill, (ii) empirical specification à la Burchardi et al. (2020), (iii) reduced form approach using the imputed share of immigrant directly in OLS estimation, (iv) first- and long difference specification.

Alternative definition of workers skill. In table B1 we approximate the skill level of workers based on whether they are employed in techies occupation (i.e. codes 47 and 38 of the French classification of occupation, respectively "*Technitiens*" and "*Ingénieurs et cadres techniques d'entreprises*"). Results remain qualitatively identical to our baseline definition of skill level.

Alternative definition of outcome variable. In table B2 we use the number of patents per worker in the district (rather than the simple number of patents) as outcome variable. This normalization does not alter our baseline results: a higher share of skilled immigrant workers increases the number of patents per worker in the district.

Specification à la Burchardi et al. (2020). This check aims at testing the robustness of our result to an alternative specification of the dependent variable used in Burchardi et al. (2020). Namely, we use the 1-year change in the number of patenting per 100,000 people in the district. Results are robust to the use of such an alternative dependent variable. See table B3.

Alternative definition of explanatory variable. As a robustness check, in table B4 we use the share of high-skilled immigrants on the total skilled workers in the district. Results remain qualitatively identical to our baseline specification.

Reduced form specification. Under the exclusion restriction validity, the imputed share of tertiary educated immigrants represents an exogenous labor supply shock that can be directly used to explain the patenting activity of districts *via* OLS estimator. Also this check supports the robustness of our results. See table B5.

First-difference estimates. The first-difference approach represents an alternative way of controlling for district-specific unobservable factors affecting the patenting activity of firms across districts. The advantage of the first-difference specification is the possibility of controlling for historical pattern in the patenting activity of immigrants and native workers in each district in the period 1900-1800 and in the total number of patents in the more recent period 1980-1970. The set of controls includes: (i) the total patents registered by natives in the district over the period 1800-1900, (ii) the patents registered by foreign born inventors in each district in the period 1800-1900, and (iii) the total number of patents registered in the district over a more recent period, i.e. 1980-1960. These variables aim at controlling for the pre-trend in a pretty exogenous way (sufficient time lag). This is the estimated equation:

$$\Delta Ln(patents)_{dt} = \beta_1 \Delta MigSh^{High}_{dt} + \Delta \mathbf{X}_{dt} + PreTrend_d + \theta_t + \epsilon_{dt} \tag{10}$$

where Δ stands for first-difference variable t - $(t-1)$. The first-difference specification goes in the direction of using the pure innovation activity of firms in each district. Indeed, taking the number of active patents in the district in first-difference corresponds to use the number of new patents in the districts. Results, reported in table B6 strongly confirm the positive effect of skilled immigrants on the patenting activity of French districts; positive yearly variations in the share of skilled immigrants have positive impact on the yearly changes in the number of patents in the district.

Long-difference estimates. An alternative approach is using long differences (i.e. difference in key variables over the entire period 1995-2010) to identify the effect of *changes* in the share of high skilled immigrants on *changes* in the patenting activity of districts. By doing so, any district-specific factor affecting both the share of skilled immigrants and the number of patents is mechanically absorbed by taking the difference. The advantage of using the long-difference specification is the possibility of controlling for historical pattern in the patenting activity of immigrants and native workers in each district in the period 1900-1800 and in the total number of patents in the more recent period 1980-1970. The estimated equation is a simple adaptation of eq. (10) where changes have been taken over the period 1995-2010, implying *de facto* a pure cross-sectional identification. Results, reported in Table B7 for skilled and techies migrant share respectively, confirm the robustness of our baseline results. Also in long-differences the share of high skilled immigrants (and techies) positively affects the change in the number of patents in each district.

Table B1: Patents and techies migrants in the district. OLS, 2SLS and IV PPML estimations

Dep var:	# Active patents in the district (ln)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Techies Migrants (sh)	0.024	0.190***	0.172***	0.211***	0.187**	0.182**	0.137*	0.203***
	(0.015)	(0.050)	(0.045)	(0.072)	(0.073)	(0.072)	(0.078)	(0.066)
Techies Natives (sh)	0.014		0.059***					
	(0.011)		(0.022)					
Estimator	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	IV PPML
$\mathbf{X}_{dt}$	No	No	No	Yes	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IV: Techies Migrant (sh)	yes	yes	yes	yes	yes	yes	yes	yes
IV: Techies Natives (sh)	no	no	no	no	no	no	no	no
Base year IV	1980	1980	1980	1980	1980	1990	1975	1980
Sample period	1995-2010	1995-2010	1995-2010	1995-2010	1995-2008	1995-2010	1995-2010	1995-2010
Observations	1,504	1,504	1,504	1,504	1,316	1,504	1,504	1,504
Cluster	dep	dep	dep	dep	dep	dep	dep	dep
F-test first stage		7.869	7.718	6.239	4.256	6.485	7.164	
Coeff first stage Mig sh		1.566***	1.726***	1.588***	2.054**	0.977**	1.412***	1.588**

Note: Dependent variable is the log of the number of active patents in the districts. Standard errors adjusted for clustering by district. ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels respectively.

Table B2: Patents per worker and high skilled migrants in the district. OLS and 2SLS estimations.

Dep var:	# Active patents per worker in the district						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
High Skill Mig. (sh)	0.003*	0.020***	0.019***	0.017***	0.018***	0.108***	0.080**
	(0.002)	(0.006)	(0.005)	(0.006)	(0.005)	(0.026)	(0.032)
High Skill Nat. (sh)	0.013						
	(0.012)						
VA per firm (ln)			-0.095***	-0.103**	-0.590	-0.253	-0.316
			(0.034)	(0.044)	(0.536)	(0.393)	(0.383)
Capital/VA			0.001	0.005	0.164	0.125	0.127
			(0.010)	(0.011)	(0.153)	(0.122)	(0.118)
Tot VA (ln)			0.030	0.048*	0.076	-0.070	0.098
			(0.025)	(0.028)	(0.620)	(0.479)	(0.490)
Estimator	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Region Fixed Effects	No	No	No	No	No	No	No
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IV: High Skill Mig. (sh)	no	yes	yes	yes	yes	yes	yes
IV: High Skill Nat. (sh)	no	no	no	no	no	no	no
Base year IV	1980	1980	1980	1980	1990	1975	1980
							Alternative shift IV
Sample period	95-10	95-10	95-10	95-08	95-10	95-10	95-10
Observations	1,504	1,504	1,504	1,504	1,316	1,504	1,504
Cluster	dep	dep	dep	dep	dep	dep	dep
F-test first stage		14.66	14.95	8.507	15.27	18.57	7.32
Coeff first stage Mig sh		2.589***	2.612***	3.029***	1.612***	2.324***	2.324***

Note: Dependent variable is the number of active patents per manufacturing worker in the districts. Standard errors adjusted for clustering by district. ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels respectively.

Table B3: Patents and high skilled immigrants in the district. Robustness check using 1-year change in the number of patents per 100,000 people.

Dep var:	1-year diff. in patenting per 100,000 people		
	(1)	(2)	(3)
High Skill Migrant (sh)	0.096	0.846***	0.887***
	(0.146)	(0.243)	(0.359)
Estimator	OLS	2SLS	2SLS
$\mathbf{X}_{dt}$	No	No	Yes
District Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
IV: High Skill Mig		Yes	Yes
Base year IV		1980	1980
Observations	1,410	1,410	1,410
Coeff first stage		2.663***	2.708***
F-test first stage		14.78	15.62

Note: The dependent variable is the 1-year change in the patenting activity per 100,000 inhabitants in the districts. Explanatory variable and IV in units. Standard errors adjusted for clustering by district. ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels respectively.

Table B4: Patents and high skilled migrants in the district. OLS and 2SLS estimations.

Dep var:	# Active patents in the district (ln)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
High Skill Mig. (sh of High Skill)	0.005	0.114***	0.114***	0.138***	0.100***	0.079***	0.174***
	(0.005)	(0.028)	(0.029)	(0.048)	(0.028)	(0.035)	(0.061)
VA per firm (ln)			-0.557	-1.318**	-0.549	-0.538	-0.588
			(0.441)	(0.653)	(0.418)	(0.390)	(0.565)
Capital/VA			0.065	0.130	0.074	0.086	0.0305
			(0.147)	(0.194)	(0.141)	(0.133)	(0.192)
Tot VA (ln)			-0.078	0.590	0.005	0.127	-0.429
			(0.572)	(0.740)	(0.545)	(0.540)	(0.761)
Estimator	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IV: High Skill Mig. (sh)	no	yes	yes	yes	yes	yes	yes
Base year IV		1980	1980	1980	1990	1975	1980
							Alternative shift IV
Sample period	95-10	95-10	95-10	95-08	95-10	95-10	95-10
Observations	1,504	1,504	1,504	1,316	1,504	1,504	1,504
Cluster	dep	dep	dep	dep	dep	dep	dep
F-test first stage		8.343	7.952	3.922	7.861	9.010	3.533
Coeff first stage Mig sh		1.531***	1.649***	1.623**	0.960***	1.529***	35.887***

Note: Dependent variable is the log of the number of active patents in the districts. Standard errors adjusted for clustering by district. ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels respectively.

Table B5: Patents and high skilled migrants in the district. Reduced form specification using the imputed share of skilled immigrants as main explanatory variable in OLS estimations.

Dep var:	# Active patents in district (ln)		
	(1)	(2)	(3)
High Skill Imputed Migrant (sh)	0.335***	0.177***	0.193***
	(0.081)	(0.042)	(0.072)
Estimator	OLS	OLS	OLS
$\mathbf{X}_{dt}$	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Base year for Imputed Migrant	1980	1990	1975
Observations	1,504	1,504	1,504
Cluster	dep	dep	dep

Note: Dependent variable is the log of the number of active patents in the districts. Standard errors adjusted for clustering by district. ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels respectively.

Table B6: Patents and high skilled migrants in the district. 2SLS first difference specification.

Dep var:	Δ # Active patents in the district (ln)			
	(1)	(2)	(3)	(4)
Δ High Skill Migrants (sh)	0.266***	0.268***		
	(0.051)	(0.074)		
Δ Techies Migrants (sh)			0.659***	0.724***
			(0.161)	(0.255)
Δ Patents Nat 1900-1800		-0.005		-0.003
		(0.005)		(0.005)
Δ Patents Mig 1900-1800		0.001		-0.002
		(0.006)		(0.008)
Δ Tot Patents 1980-1970		0.013		0.019
		(0.013)		(0.017)
Estimator	2SLS	2SLS	2SLS	2SLS
$\mathbf{X}_{dt}$	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
IV: High Skill Mig (sh)	Yes	Yes	Yes	Yes
Base year IV	1980	1980	1980	1980
Observations	1,410	1,410	1,410	1,410
Cluster	dep	dep	dep	dep
F-test first stage	56.57	25.99	18.11	7.523
Coeff first stage	1.657***	1.535***	0.670***	0.569***

Note: Dependent variable is the difference in the log of the number of active patents in the districts. Standard errors adjusted for clustering by district. ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels respectively.

Table B7: Patents and high skilled migrants in the district. 2SLS long difference specification.

Dep var:	Δ # Active patents in the district (ln)			
	(1)	(2)	(3)	(4)
Δ High Skill Migrants (sh)	0.199***	0.204***		
	(0.052)	(0.062)		
Δ Techies Migrants (sh)			0.375***	0.379***
			(0.107)	(0.115)
Δ Patents Nat 1900-1800		-0.054		-0.066
		(0.064)		(0.066)
Δ Patents Mig 1900-1800		0.014		0.024
		(0.067)		(0.066)
Δ Tot Patents 1980-1970		0.092		0.101
		(0.107)		(0.112)
Estimator	2SLS	2SLS	2SLS	2SLS
$\mathbf{X}_{dt}$	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No
IV: High Skill Mig (sh)	Yes	Yes	Yes	Yes
Base year IV	1980	1980	1980	1980
Observations	94	94	94	94
Cluster	dep	dep	dep	dep
F-test first stage	26.06	36.48	16.42	25.51
Coeff first stage	2.088***	2.197***	1.107***	1.180***

Note: Dependent variable is the difference in the log of the number of active patents in the districts. Standard errors adjusted for clustering by district. ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels respectively.

C Firm level evidence: robustness checks.

This section contains a battery of checks showing the robustness of our baseline (firm-level) results. First, we show a robustness check using the firm-level share of immigrants as main explanatory variable. This is instrumented by the imputed share of immigrants in the district as discussed in section 5.1. Results reported in table C1 show the robustness of our results. Second, we show whether our results are driven by firms located in very large cities (such as Paris, Marseilles and Lyon). See table C2. Third, we test the scale effect of migration shock, and use the number of skilled immigrants and natives (in turn) as main dependent variable. See table C3. The negative/null effect of migration shocks on the number of natives employed in the firms suggests the absence of a scale effect driving our main results (i.e. the migration-innovation nexus does not reflect a mere scale-up of the firm). Finally, in Figure C1 we report the 2SLS firm level estimates excluding one sector at the time. The point estimates on the share of skilled immigrants do not change, showing that our baseline results are not driven by any individual sectors.

Table C1: High skilled migrants and firms' patenting activity using firm-specific share of immigrants as explanatory variable.

Dep var:	# Active patents in the firm (ln)				
	(1)	(2)	(3)	(4)	(5)
High Skill Migrant in firm (sh)	0.001	0.132**	0.149***	0.144***	0.161**
	(0.001)	(0.054)	(0.058)	(0.055)	(0.063)
Estimator	OLS	2SLS	2SLS	2SLS	2SLS
$\mathbf{X}_{it}$	No	No	Yes	Yes	Yes
Firm-District Fixed Effects	Yes	Yes	Yes	Yes	Yes
Sector-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
IV: High Skill Mig (sh)	No	Yes	Yes	Yes	Yes
Base year IV		1980	1980	1975	1990
Observations	51,704	51,704	51,704	51,704	51,704
Cluster	id rt	id rt	id rt	id rt	id rt
F-test		13.9	13.35	14.04	11.98
First stage High Skill Mig in district		0.761***	0.752***	0.476***	0.626***

Note: Dependent variable is the log of the number of active patents in the firm. Standard errors adjusted for clustering by firm and region-year. ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels respectively.

Table C2: High skilled migrants and firms' patenting activity by district of firm localization. OLS and 2SLS. Within specification.

Dep var:	# Active patents in the firm (ln)	
	(1)	(2)
High Skill Migrant (sh)	0.013***	0.066***
	(0.005)	(0.014)
High Skill Migrant (sh) × Big City	-0.000	-0.020
	(0.008)	(0.016)
Estimator	OLS	OLS
$\mathbf{X}_{it}$	Yes	Yes
Firm-District Fixed Effects	Yes	Yes
Sector-Year Fixed Effects	Yes	Yes
IV: High Skill Mig (sh)	No	Yes
Base year IV		1980
Observations	51,704	51,704
Cluster	id rt	id rt
F-test		59.20
Coeff first stage High Skill Mig		3.664***
Coeff first stage Interaction		2.351***

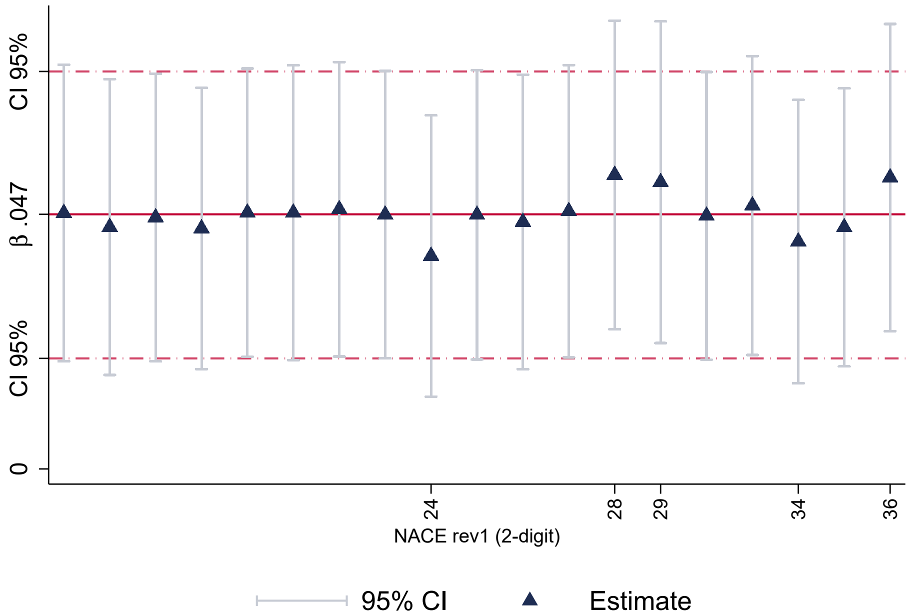
Note: Dependent variable is the log of the number of active patents in the firm. Big cities districts are: Paris, Lyon and Marseilles. Standard errors adjusted for clustering by firm and region-year. ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels respectively.

Table C3: The impact of migrants on the *number* of native and immigrant skilled workers in the firm.

Dep var:	# Skilled Migrants		# Skilled Natives		# Techies Migrants		# Techies Natives	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High Skill Migrant (sh)	0.053***	0.059***	-0.015	0.006	0.052***	0.056***	-0.036***	-0.014
	(0.013)	(0.013)	(0.012)	(0.009)	(0.013)	(0.013)	(0.012)	(0.010)
Estimator	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
$\mathbf{X}_{it}$	No	Yes	No	Yes	No	Yes	No	Yes
Firm-District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IV: High Skill Mig (sh)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Base year IV	1980	1980	1980	1980	1980	1980	1980	1980
Observations	51,704	51,704	51,704	51,704	51,704	51,704	51,704	51,704
Cluster	id rt	id rt	id rt	id rt	id rt	id rt	id rt	id rt
F-test first stage	258.6	257.5	258.6	257.5	258.6	257.5	258.6	257.5

Note: Dependent variables are the number of native and immigrant skilled workers employed in the firm. Standard errors adjusted for clustering by firm and region-year. ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels respectively.

Figure C1: Estimated impact by excluding one sector at a time.



Source: Authors calculations DADS data. *Note*: The graph reports the estimated coefficients of the High Skill immigrant share from the second stage regression where the NACE 2-digit sector (reported in the horizontal axis) is excluded. Whiskers display 95% confidence intervals ($\pm 1.96 * SE$), where standard errors, SE, are two-way clustered at the firm and region-year level.

D Derivation optimal immigrant-native ratio

This section provides more details on the derivation of the optimal native-immigrant ratio discussed in section 7.1. We start by the equation 5 reporting each occupation specific output in per worker terms:

$$q_o = \frac{Q_o}{L_o^I + L_o^D} = \left[\left(A_o^I sh_o \right)^{\frac{\rho-1}{\rho}} + \left(A_o^D (1 - sh_o) \right)^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}} \quad \text{with } o = T, M. \tag{11}$$

The share of immigrant workers in occupation o that maximizes each occupation's efficiency in production is obtained by equating the partial derivative of q_o to zero (i.e. $\partial q_o / \partial sh_o = 0$):

$$\left[\frac{\rho - 1}{\rho} \left(A_o^I sh_o \right)^{-1/\rho} A_o^I - \frac{\rho - 1}{\rho} \left(A_o^D - A_o^D sh_o \right)^{-1/\rho} A_o^D) \right] = 0 \tag{12}$$

$$\left(A_o^I sh_o \right)^{-1/\rho} A_o^I = \left(A_o^D - A_o^D sh_o \right)^{-1/\rho} A_o^D \tag{13}$$

$$\frac{A_o^I}{A_o^D} = \left[\frac{A_o^D - A_o^D sh_o}{A_o^I sh_o} \right]^{-\frac{1}{\rho}} \tag{14}$$

$$\left[\frac{A_o^I}{A_o^D} \right]^{\rho-1} = \frac{sh_o}{1 - sh_o} \tag{15}$$

by simply noticing that $sh_o = L_o^I / \left(L_o^I + L_o^D \right)$ and $1 - sh_o = L_o^D / \left(L_o^I + L_o^D \right)$ the optimal immigrant-to-native ratio in occupation o can be expressed as follows:

$$\left[\frac{A_o^I}{A_o^D} \right]^{\rho-1} = \frac{L_o^I / \left(L_o^I + L_o^D \right)}{L_o^D / \left(L_o^I + L_o^D \right)} = \frac{L_o^I}{L_o^D} \tag{16}$$

The same conclusion holds by considering the share of immigrants over the total employment in occupation o (sh_o), rather than the immigrant-to-native ratio (L_o^I / L_o^D), as a proxy for firm's task allocation. Indeed, equation (15) can be re-arranged as follows:

$$\left[\frac{A_o^I}{A_o^D} \right]^{\rho-1} (1 - sh) = sh \tag{17}$$

$$\left[\frac{A_o^I}{A_o^D} \right]^{\rho-1} = sh + sh \left[\frac{A_o^I}{A_o^D} \right]^{\rho-1} \tag{18}$$

And finally:

$$sh_o = \frac{\left[\frac{A_o^I}{A_o^D}\right]^{\rho-1}}{1+\left[\frac{A_o^I}{A_o^D}\right]^{\rho-1}} \tag{19}$$

Both the optimal immigrant-to-native ratio (L_o^I/L_o^D) and the share of immigrants over the total employment in occupation o (sh_o) depend on the structure of comparative advantages of immigrant and native skilled workers in technical *vs* managerial tasks.

E Robustness checks on the mechanism

In tables E1-E4 we provide some robustness checks on the task reallocation channel. Namely, table E1 shows the positive effect of a skilled immigrant worker supply shock on the share of immigrants workers allocated in techies occupation in the firm. Table E2 shows the effect of skilled immigrant workers on the allocation of native workers towards language-intensive tasks. Table E3 shows the robustness of our re-allocation mechanism to an alternative measure of tasks reallocation (i.e. managerial-to-technical ratio by type of workers). An exogenous inflow of skilled immigrants makes firms allocating native workers more intensively in managerial occupations. Table E4 shows the effect of skilled immigration on the managerial-to-technical ratio of natives (first stage), and this on the patenting of firms.

Table E1: High skilled migrants and the share of migrants employed in techies occupations.

Dep var:	Share of migrants in technical occupation (over total techies workers)			
	(1)	(2)	(3)	(4)
High Skill Migrants (sh)	0.287***	0.285***	0.398**	0.385**
	(0.101)	(0.100)	(0.166)	(0.168)
Estimator	OLS	OLS	2SLS	2SLS
$\mathbf{X}_{it}$	No	Yes	No	Yes
Firm-District Fixed Effects	Yes	Yes	Yes	Yes
Sector-Year Fixed Effects	Yes	Yes	Yes	Yes
IV: High Skill Migrant (sh)	No	No	Yes	Yes
Base year IV			1980	1980
Observations	41,837	41,837	41,837	41,837
Cluster	dep	dep	dep	dep
F-stat first stage			253.5	251.8

Note: Dependent variable is the share of migrants employed in techies occupation in the firm. Control variables in $\mathbf{X}_{it}$ included in columns 2 and 4. Standard errors adjusted for clustering by department. ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels respectively.

Table E2: High skilled migrants and the share of natives employed in each firm's type of occupation (broad and narrow definition). 2SLS estimations.

	Panel a: broad definition of occupation					
Dep var:	Produc. workers (share over tot natives)		Interm. Profession (share over tot natives)		Management (share over tot natives)	
	(1)	(2)	(3)	(4)	(5)	(6)
High Skill Migrants (sh)	-0.450**	-0.324*	-0.100	-0.135	0.551***	0.459**
	(0.177)	(0.177)	(0.157)	(0.161)	(0.172)	(0.181)
	Panel b: narrow definition of occupation					
Dep var:	Sales Executives (share over tot natives)		Engineers (share over tot natives)		Other Profess. (share over tot natives)	
High Skill Migrants (sh)	0.276**	0.241**	0.174*	0.161	0.101	0.057
	(0.115)	(0.117)	(0.100)	(0.104)	(0.066)	(0.067)
Estimator	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
$\mathbf{X}_{it}$	No	Yes	No	Yes	No	Yes
Firm-District FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
IV: High Skill Mig. (sh)	Yes	Yes	Yes	Yes	Yes	Yes
Base year IV	1980	1980	1980	1980	1980	1980
Observations	51,064	51,064	51,064	51,064	51,064	51,064
Cluster	id rt	id rt	id rt	id rt	id rt	id rt
F-test first stage	266	264.9	266	264.9	266	264.9

Note: Dependent variable is the share of natives employed in each firm's layer over total firm's native workers. Control variables in $\mathbf{X}_{it}$ included in columns 2, 4 and 6. Standard errors adjusted for clustering by firm and region-year. ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels respectively.

Table E3: High skilled migrants and the ratio of native workers employed in technological versus communication intensive occupations.

Dep var:	Ln(Com / Techies workers)				
	Total	*Migrants*	*Natives*		
	(1)	(2)	(3)	(4)	(5)
High Skill Migrants (sh)	0.020*	-0.009	0.019*	0.018*	0.021*
	(0.011)	(0.010)	(0.011)	(0.010)	(0.011)
Estimator	2SLS	2SLS	2SLS	2SLS	2SLS
$\mathbf{X}_{it}$	Yes	Yes	Yes	Yes	Yes
Firm-District FE	Yes	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes	Yes
IV: High Skill Mig (sh)	Yes	Yes	Yes	Yes	Yes
Base year IV	1980	1980	1980	1990	1975
Observations	51,704	51,704	51,704	51,704	51,704
Cluster	id rt	id rt	id rt	id rt	id rt
F-test first stage	257.5	257.5	257.5	216.5	271.8

Note: Dependent variable is the log of the ratio between Technical and Communication workers for each worker category (i.e. total, migrant and natives). Controls variables in $\mathbf{X}_{it}$ always included. Standard errors adjusted for clustering by firm and region-year. ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels respectively.

Table E4: High skilled migrants and the patenting activity of firms *via* the tasks reallocation channel. 2SLS estimations.

Dep var:	# Active patents in the firm			
	(1)	(2)	(3)	(4)
Ln(Com/Tech workers)$_{natives}$	1.659***	1.702***	1.572***	2.743*
	(0.619)	(0.642)	(0.572)	(1.406)
Estimator	2SLS	2SLS	2SLS	2SLS
$\mathbf{X}_{it}$	No	No	No	Yes
Firm-District FE	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes
IV: Com/Tech workers (ln)	Yes	Yes	Yes	Yes
Base year IV	1980	1975	1990	1980
				No Franco. Mig
Observations	51,704	51,704	51,704	51,704
Cluster	id rt	id rt	id rt	id rt
Coeff first stage	0.061***	0.053**	0.039***	0.038*
F-test	6.870	6.700	7.368	2.994

Note: Dependent variable is the number of active patents in the firm (ln). Standard errors adjusted for clustering by firm and region-year. ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels respectively.