Skilled Immigration, Task Allocation and the Innovation of Firms*

Anna Maria Mayda (Georgetown University and CEPR)†

Gianluca Orefice (University Paris-Dauphine, PSL)‡ Gianluca Santoni (CEPII)§

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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. The arrival of skilled immigrants pushes French skilled workers towards language-intensive, managerial tasks while foreign skilled workers specialize in technical, research-oriented tasks. Through this channel, greater innovation is the result of productivity gains from specialization.

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†amm223@georgetown.edu

‡gianluca.orefice@dauphine.psl.eu

§gianluca.santoni@cepii.fr

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, there are skilled migrants in Europe and their number is going up in some countries. 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]

France does not have a large program explicitly targeted at attracting skilled migrants – like the H-1B visas program in the U.S..[2] 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.

Recent contributions point out that skilled immigration has greatly contributed to innovation and patenting activity (see for example Hunt & Gauthier-Loiselle (2010), Kerr & Lincoln (2010)). Yet most papers focus on the U.S. and often use aggregate data or small samples of firm-level data.[3] Europe has been 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. In this paper we provide evidence on the link between immigration and innovation in the European context. We use

[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] 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.

[3] A notable exception from this point of view is Burchardi, Chaney, Hassan, Tarquinio & Terry (2020).

information on the universe of French firms spanning the period between 1995 and 2010 and investigate the impact of skilled migration to France on patenting activity.

We estimate a causal effect of skilled migration on innovation activity in France. We find that, between 1995 and 2010, an increase in the share 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 share of skilled immigrants in a district led to an increase, on average, of 2.6 patents per 10,000 workers. Importantly, we instrument for the share of skilled migrants using a modified version of the Card instrument and provide evidence for the exclusion restriction by carrying out a pre-treatment trend exercise. Moreover, we check the robustness of our results with respect to the exclusion restriction (Conley, Hansen & Rossi 2012). When we control for the (instrumented) share of skilled native workers, 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.[4] 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 re-organization of tasks – by which skilled native workers specialize in communication-

[4]We control for the skilled native share only in the specifications without district fixed effects. When we include district fixed effects, we cannot nor need to control for the high-skilled native share because: the instrument-predicted skilled native share is almost entirely absorbed by district and year fixed effects; controlling for district fixed effects, the distribution of skilled immigrants is orthogonal to the distribution of skilled French workers, which implies that omitting the latter does not create an omitted variable bias. See detailed discussion on this point in section 6.1.

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. Such a 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 Ecoles* system) is set up in such a way that outsiders (both French workers who did not attend the *Grandes Ecoles* and foreign workers who studied abroad) are less likely to have access, in practice, to high-hierarchy positions (i.e *cadres*) within firms.

The contribution to the previous literature is twofold. First, to the best of our knowledge, this is the first paper that explores the migration-innovation nexus using firm level data for a EU country. 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 on migration policy in France. Second, this is the first paper that directly test the micro-level mechanism underlying the migration-innovation nexus and applies the tasks specialization idea to innovation (other mechanisms such as the knowledge diffusion channel have only been tested at the aggregate level).

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. 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.[5] Hunt & Gauthier-Loiselle (2010) exploit variation

[5] A firm level perspective has 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

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.[6] 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. 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. 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. 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. An important recent contribution to the literature is the work by Doran, Gelber & Isen (2014), 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

effect magnified for initially less productive and less capital-intensive firms.

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

Italy are low-skilled.

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 firm-specific mechanism of 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, 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.

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 immigration zero 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 yet another policy shift. Right after becoming Prime Minister in 1997, 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.[7]

Next, in the mid-2000's, came another shift in France's approach to immigration, with Interior Minister and later President Nicolas Sarkozy, this time towards a policy of chosen/selective immigration (ЛҞЛҞ*immigration choisie*"). The latter is a clear departure from past French migration policies of zero immigration zero. The goal of the policy of immigration choisie is to: 1) fight irregular migration; 2) decrease family migration; 3) increase labor migration targeting particular migrants and encouraging

[7] Bertossi (2008) explains: "Between 1998 and 2004,ЛҞЛҞopposability 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 вЃY against 35,000 IT workers needed according to estimates of the ЛҞЛҞSyntec Informatic" professional organisation (Le Monde 2001). Another decree from the Ministry of Labour in March 2004 facilitates and shortens the procedure for foreign вЃЧwhite collarsвЃЄ."

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: ЛІКЛІКlow 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 sectors)." See Bertossi (2008), page 9.[8].

Immigrants' labor-market access in Sarkozy's 2006 policy of "*immigration choisie*" depended 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 ЛІКЛІКnew" EU Member States of the 2004 and 2007 EU enlargements with exceptions for 150 occupations (and immigrants from Cyprus and Malta).[9] France applied temporary restriction measures until May, 1, 2009 for 8 of the 2004 ЛІКЛІКnew" member states, and until January, 1, 2012 for Bulgaria and Romania.[10]

To conclude, France's approach to immigration has shifted from very restrictive in the 1970s up to 1997, to less so, in terms of the size of immigrant flows, with a much greater emphasis, in the last twenty years, on skills and migrants' selection. Our approach in this paper is to take note of the iter of French migration policy in our period of analysis, especially as far as skilled migrants are concerned. However, ultimately, what matters empirically is the actual changes in skilled immigrant flows produced by these policy shifts, as evidenced in the data. This 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* вЃY DADS), (ii) balance sheet information (FICUS/FARE), (iii) firm

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

[9]The Accession Treaty of 2003 gave the possibility to the ЛІКЛІКold" member states to temporarily restrict (for a maximum of 7 years) the access to their labor markets to citizens from ЛІКЛІКnew" 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 ЛІКЛІКold" 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.

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

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).

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 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).[11] Each worker is associated to an employer (identified by a unique identification 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. 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 to measure the immigrant labor supply over the period 1995-2010 may imply a measurement error in estimations (nationality *vs* country of birth based definition of immigrants status). Although year fixed effects will control for this discontinuity in the definition of migrant worker 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 adopted to calculate the number of immigrant workers in the district.

The education of workers is not directly available from DADS data.[12] We infer the skill level of workers from their occupation. Namely, we employ a specific occupation-education matching based

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

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

on the International Standard Classification of Occupations ISCO, that assigns a specific education level to each one-digit ISCO occupation code.[13] Details on how each specific occupation is matched to an education level are reported in table A1. However, the matching based on 1-digit ISCO category may be imprecise, and some skilled workers may be classified low-skilled simply because belonging to a broad low-skilled 1-digit ISCO code. Hence, to reduce concerns on 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 are those in PCS occupation 47 ("*Techniciens*") and 38 ("*Ingénieurs et cadres techniques d'entreprise*"). Based on these two definitions of low- and skilled workers, we computed the share of migrant and native skilled workers in each district-year for 94 French district over the period 1995-2010.[14] All in all, our district-specific estimation sample includes 1,504 observations, while the firm-specific estimation sample includes 51,704 firm-year observations with an average share of skilled migrant and native workers of 2.7% 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 controls 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) in firm-specific 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.[15] Table 1 shows the large dispersion in patenting activity across French firms: the average number of

[13]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 information.

[14]Because of limited availability in the historical settlement of immigrants in overseas French districts (used to build the instrumental variable in section 5.1), we limit our analysis to 94 mainlands' districts.

[15]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.

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. Information on the historical innovation activity of French districts (used to control explicitly for the pre-trend) is publicly accessible via the INPI.[16] The database includes detailed information on more than 400 thousand patents from 1791 to 1902.

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
		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

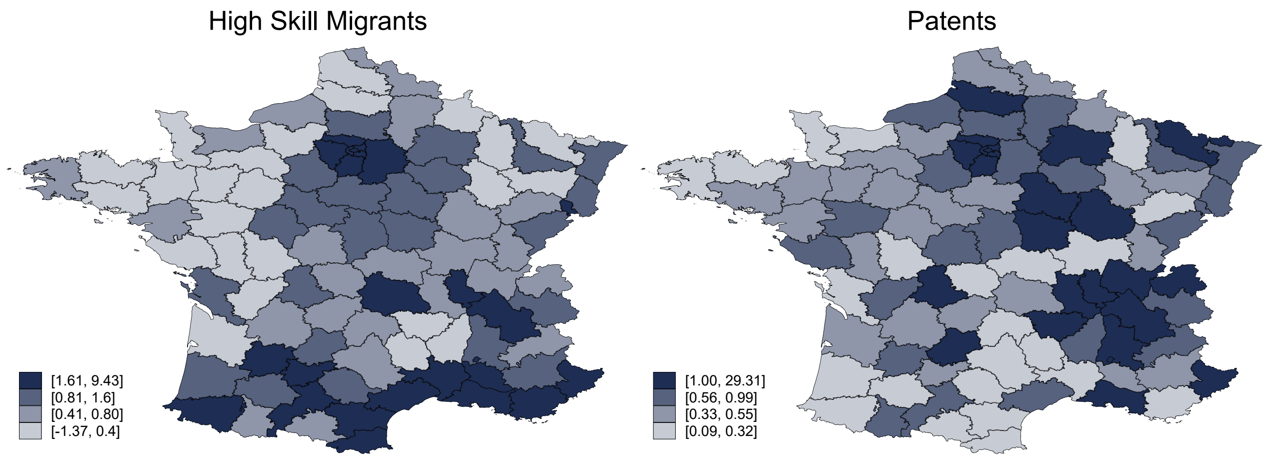
Source: authors' calculation on DADS and FICUS/FARE data.

In figure 1 we show the 1995-2010 change in the share of skilled immigrant workers and patent intensity (i.e. patent per worker) across French districts. The map on the left shows the change in the share of skilled immigrant workers across districts (as percentage of total workforce). The map on the right shows the geographical distribution of the change in the number of patents per worker (i.e. share between the number of patents and workers in the district). It clearly emerges that the endowment of skilled immigrants increased in particular around the largest French cities such as Paris (*Ile de France*), Lyon (*Rhône*) and Toulouse (*Haute Garonne*), and in south-coastal districts. Over the period of analysis, we observe a reduction (increase) in the share of skilled immigrants localized in northern (southern) districts. In terms of patenting activity, the districts of the *Auvergne-Rhône-Alpes* region experienced a marked increase in patents *per capita*. The cross-districts and over-time variation in

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

both skilled immigrants intensity and patenting activity of districts (and firms) will be at the core of the empirical strategy discussed in the next section. Table A2 shows the constant increase in the share of immigrant workers residing in France over the last forty years (based on French Census data).[17]

Figure 1: Share of skilled immigrant workers (left-side) and patents per workers (right-side) across French districts. Change in the period 1995-2010.



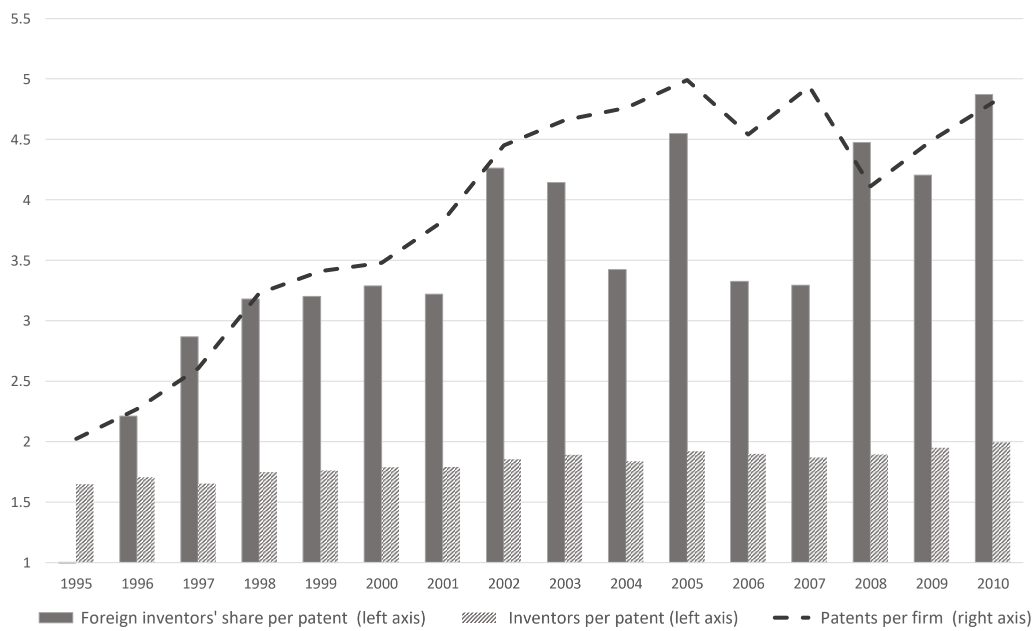
Source: Authors calculations on Orbis and DADS data. Notes: the four bins (i.e. colours) characterizing the change in the share of high-skill migrants and the patenting activity of districts reflect the four quartiles of the underlying distribution: (i) change above the 75^{th} percentile of the sample distribution (dark blue), (ii) changes comprised between the 75^{th} percentile and the median (medium-dark blue), (iii) changes comprised between the median and the 25^{th} percentile of the sample distribution (light blue), and (iv) changes below the 25^{th} percentile of the sample distribution (yellow). Districts of Lozère (48) and Tarn-et-Garonne (82) have zero patents in 1995.

The increase in the availability (share) of skilled migrant workers observed in the period 1995-2010 reflects into the increase in the share of foreign inventors per patent showed in figure 2 (dark grey bars). Interestingly, over the same time period the size of patenting teams (i.e. inventors per patent) remained almost unchanged (light grey bars in figure 2), and the number of patents per firm considerably increased. Taken together, these qualitative evidences suggest: (i) a change in the composition of patenting teams (more immigrant intensive) and (ii) a positive correlation between the share of foreign inventors in patenting team and the patenting activity of firms. The change in the skilled workforce composition of French firms is also showed in table 2, where we report the evolution over time in the share of skilled *native* workers for firms having respectively increasing, decreasing and constant endowment of skilled *migrant* workers. Interestingly, for firms employing an increasing number of skilled (or techies) immigrant workers over the period 1996-2010, the share of skilled natives decreases over time. Conversely, firms whose endowment of skilled immigrants does not change over time do not experience

[17]In figure A1 we show the increase in the share of skilled workers in France and other European countries.

any change in the share of natives employed in skilled tasks. Two interesting features emerge from table 2. First, French firms experienced a change in the composition of their skilled workforce (not just an increase in the scale of skilled workers in production). Second, in absence of positive skilled migrant labor supply shocks firms may keep unchanged the within-firm allocation of tasks.

Figure 2: Trend in the average size of innovation teams in France (number of inventors per patent) and average share of foreign inventors per patent.



Source: Authors calculations DADS and ORBIS data. Weighted Averages using firm value added shares.

Table 2: Share of skilled (and techies) native workers in firms with increasing, decreasing and constant number of skilled (and techies) immigrant workers.

	Avg share skilled native workers				Avg change
Firms with:	*1996*	*2000*	*2005*	*2010*	*(1996-2010)*
Increasing share of skilled immigrants	90.8	90.0	74.1	85.8	-8.6%
Constant share of skilled immigrants	98.2	98.4	98.7	95.1	0.0%
Decreasing share of skilled immigrants	95.1	93.8	97.6	92.9	9.4%
	Avg share techies native workers				Avg change
Firms with:	*1996*	*2000*	*2005*	*2010*	*(1996-2010)*
Increasing share of techies immigrants	91.2	89.7	68.8	84.4	-9.7%
Constant share of techies immigrants	98.6	98.6	98.8	95.9	0.0%
decreasing share of techies immigrants	94.1	93.4	97.3	93.6	11.4%

Notes: each entry reports the average share of skilled (techies) native workers within a given sub-sample of firms; with sub-sample based on changes in the endowment of skilled migrants. Source: authors' calculation on DADS data.

5 Empirical strategy

This section tests the effect of the presence of skilled migrants in each local labor market (here approximated by French district or *département*)[18] on the patenting activity of both French districts (i.e. results discussed in section 6.1) and firms (i.e. results discussed in section 6.2). The two empirical specifications, respectively at district and firm level, are the following:

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

$$Y_{i\in d,t} = \theta_{id} + \theta_{st} + \beta_1 MigSh_{dt}^{High} + \mathbf{X}_{it} + \epsilon_{idt} \tag{2}$$

where the subscript d, i, s and t stand respectively for districts, firm (localized in district d),[19] firm's sector and year. Our dependent variable is the (logarithm of) active patents in each district (eq. 1) and firm (eq. 2). To avoid the problem of zeros in the number of patents in districts and firms we adopt the inverse hyperbolic transformation. In a robustness check reported in appendix section B we alternatively use a first- and long difference approach and express our dependent variable in log-difference (as in Bool et al. 2015). In table B2 we use the number of patents *per worker* in the district as a outcome variable. Moreover, in table B3 we follow Burchardi et al. (2020) and use the 1-year change in the number of patents per 100,000 people in the district as dependent variable. The key variable of interest is the share of skilled migrant workers over total workers in the districts $MigSh_{dt}^{High}$. As a robustness check, in table B4 we use the share of skilled immigrant over total skilled workers in the district. The sets of fixed effects θ_d, θ_t, θ_{id}, θ_{st} and control variables $\mathbf{X}_{dt}$ and $\mathbf{X}_{it}$ aimed at reducing the omitted variable bias depend on the geographical unit of analysis (district or firm) and discussed in details in the dedicated sections 6.1 and 6.2.

Although the information on the number of immigrant workers is available also at firm level, our main explanatory variable is the *district*-specific share of skilled immigrants. We do so for three reasons. First, the firm-specific share of immigrant is the result of a firm-specific decision process which

[18] We approximate the local labor market with French *département* rather than smaller geographical units (such as commuting zones or *zone d'emploi*) for two reasons. First, to build the IV we need information of the geographical distribution of immigrants back in the 1980 and this is available at districts (not commuting zone) level. Second, by taking smaller geographical units would imply an inflation of zero (or very small numbers) in the share of skilled immigrant workers.

[19] 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.

is unobservable (i.e. quality of management and/or human resources division), and as such highly endogenous. Second, while the exclusion restriction on a district specific shift-share IV is plausible and can be qualitatively tested (see pre-trend tests in the next section), the exclusion restriction for firm specific shift-share IV is hard to test. Third, we are prevented to build a firm-level shift-share IV because of missing information on firms' workforce composition by origin country in the pre-1995 period. In using district-specific skilled migrant supply shocks we make the implicit assumption that these shocks push the firms to increase their endowment of immigrants. Table A3 empirically supports this implicit assumption. Positive changes in the share of skilled immigrants in the district cause (2SLS approach used) positive changes in the number of immigrant skilled workers employed in the firm. Moreover, in the appendix section C we replicate our baseline results using the *firm-level* share of skilled immigrants as a main explanatory variable, instrumenting it with the district-specific shift-share imputed immigrant share. Our results hold.

5.1 Endogeneity and Instrumental Variable

In assessing the causal impact of skilled immigrant workers on the patent 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 estimations (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 omitted, and calls for the adoption of an Instrumental Variable approach in order to address any residual endogeneity concern.

We adopt the shift-share methodology to build the Instrumental Variable for the share of skilled immigrant workers in each local labor market. We first calculate the share of *high skilled* immigrant workers (M) by origin (o) residing in each French district (d) in 1980 as follows:

$$sh^M_{d,o,1980} = \frac{M_{d,o,1980}}{\sum_d M_{d,o,1980}} \quad .$$

We obtain the *imputed* number of skilled immigrant workers in the district by multiplying the origin-specific aggregate levels of immigrant population in France (M_{ot}) by the 1980 shares of that immigrant population across districts ($sh^M_{d,o,1980}$). As robustness checks we alternatively use the geographic distribution of immigrants in 1975 and 1990 to allocate time-varying aggregate immigrants shocks.The predicted number of skilled immigrants (M) in district d is given by the following equation:

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

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 $\left(\widehat{M_{dt}}/(\widehat{N_{dt}} + \widehat{M_{dt}})\right)$.[20] In what follows we propose a battery of tests aimed to support the validity of our IV (pre-trend, plausible exogeneity and Rotemberg weights based validity test), along with alternative specification of our IV for robustness.

Validity of IV. In Table 3 we support the validity of our IV by showing the absence of correlation between the pre-1995 trend 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). The absence of correlation between pre-trends in the patenting activity of French districts and the shift-share instrument discussed above, reassures on the absence of unobserved and time-persistent shocks that affected the patenting activity of firms in the past and the settlement of immigrants over the period of observation.

Plausible Exogeneity. As an alternative test of the validity of our IV, we check the robustness of the coefficient of interest ($MigSh^{High}_{dt}$) 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. $\gamma \neq 0$.[21] 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

[20] When included in the regression, also the share of skilled *native* workers is likely to be endogenous. We replicate the shift-share approach to build a dedicated Instrumental Variable for the share of skilled native workers in each district. First, we calculate the share of *high skilled* natives (N) in each district in 1980 $sh^N_{d,1980} = \frac{N_{d,1980}}{\sum_d N_{d,1980}}$, then we calculate the imputed number of skilled natives in district d at time t by multiplying the share $sh^N_{d,1980}$ 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 $\left(\widehat{N}_{dt}/(\widehat{N_{dt}} + \widehat{M_{dt}})\right)$.

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

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:				
$\Delta\ IV_{2010-1995}^{America-Pacific}$	0.069	0.075	0.029	0.087
	(0.096)	(0.092)	(0.204)	(0.228)
$\Delta\ IV_{2010-1995}^{Africa}$	7.140	9.888	3.076	-3.481
	(4.900)	(5.993)	(8.096)	(7.254)
$\Delta\ IV_{2010-1995}^{Europe\&Centr.Asia}$	6.386	39.307	32.870	20.201
	(22.961	(27.540)	(41.383)	(43.974)
$\Delta\ IV_{2010-1995}^{Asia}$	-2.561	-0.560	7.341**	4.881
	(3.384)	(2.426)	(2.823)	(3.271)
$\Delta\ IV_{2010-1995}^{Europe}$	-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.

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 ($MigSh_{dt}^{High}$).[22] 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 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 (2) is robust to deviations from the perfect validity of the exclusion restriction.

Rotemberg weights based validity test. 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 those having larger impact for the identification of the 2SLS estimator. Here we follow the approach suggested by Goldsmith-Pinkham, Sorkin & Swift (2020) and calculate the Rotemberg weights associated to each macro-group of immigrants' origins. Not surprisingly, the macro-group covering the largest set of origins (i.e. American-Pacific origins) accounts the most for the overall identification of the shift-share IV (0.9 Rotemberg weights). Other origins are less important for the identification of the shift-share IV (weight 0.04 for Africa, 0.02 for Europe & Centr. Asia, 0.003 and 0.000 for respectively Asian and other European origins).[23] In Table 3 we test the exogeneity of such origin-specific migrant shares, and regress the trend in the patenting activity

[22]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).

[23]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 America-Pacific origins, 0.120 when using African countries, 0.125 for Europe & Centr. Asia origins, 0.135 for Asian origins and 0.154 for other European origins.

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 (neither less) intense patenting activity of firms across districts. Alternatively, in Table A7 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.

Alternative Instrumental Variable. As discussed in Borusyak, Hull & Jaravel (2021) the exogeneity of the shift component in eq. 3, M_{ot}, is of key importance for the validity of the shift-share IV discussed above. If unobserved French district-specific shocks attract immigrants from a specific set of origins, then the validity of the shift-share IV can be challenged. To solve this potential concern, as a robustness check, we propose an alternative shift-share IV based on extra-France immigrant inflows purged by any origin-specific linkages with France. First, we regress the origin-specific immigrant inflows in France (PPML estimator) on: (i) inflows of immigrants towards neighbor countries (excluding France), and (ii) a set of origin and year fixed effects.[24] The fit of this regression, purged by any origin- and time- specific factors (i.e. estimated fixed effects) is then used as a shift component in eq. 3. Being based on extra-France migration flows, the shift component of such an alternative IV is mechanically uncorrelated with unobserved France-specific factors, and therefore likely to satisfy the exclusion restriction.[25]

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 testing the effect of skilled immigrant workers on the number of active patents in each French district d and year t, $patents_{dt}$. With the aim of including the share

[24] France neighbor countries are Spain, Belgium, Luxembourg, Germany, Switzerland and Italy.

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

of both *immigrant* and *native* skilled workers in the same regression, we slightly modify eq. (1) and include region rather than district fixed effects.[26] 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). Table 4 shows the OLS and 2SLS results for such preliminary regression. Both migrant and native skilled workers have positive and significant effect on the patenting activity of districts. Interestingly, the point estimate associated to the share of skilled migrants is larger than for high skilled natives. This evidence holds with the alternative proxy for the skill level of workers (i.e. techies) reported in columns 3-4 of table 4.

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)		0.242		0.005

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.

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

We now move to our preferred district-specific specification, and include district fixed effects θ_d as in equation (1). We therefore explore the pure within-district variation in the number of patents and share of skilled immigrant. This drastically reduces any omitted variable (endogeneity) concern, but implies the impossibility of instrumenting the share of high skill natives. Indeed, the imputed number of high-skill natives $\widehat{N_{dt}}$ is almost entirely explained by district and year fixed effects (see the R-square of district and year fixed effects in explaining the imputed number of natives in table A4).[27] This implies a non-powerful first stage for the share of skilled natives when we include both district and year fixed effects. For this reason we omit the share of skilled natives from the 2SLS within specifications. However, omitting the share of natives from regressions does not imply a bias in the estimation of $MigSh_{dt}^{High}$. Native and immigrant skilled workers do not co-locate in the same districts, and the share of migrants does not capture the effect of skilled natives. In figure 3 we plot the percentage change over the period 1995-2010 in the (log) number of migrants (vertical axis) and native (horizontal axis) workers across districts, showing an almost null correlation between the two variables. In table A5 we refine this evidence by regressing the share of skilled immigrants on the share of skilled natives in each district-year cell controlling for district and year fixed effects (first and long differences approach are reported as a further check). Again, we find strong evidence of null correlation between the settlement of skilled immigrants and natives (if any such a correlation has a negative sign). It must be also noticed that since district and year fixed effects absorb almost the entire variability in the share of high skilled native workers (both observed and imputed, see table A4), the omitted variable concern due to the omission of the share of skilled native workers is strongly reduced. Finally, the share of high skilled natives, conditioned on district and year fixed effects, is uncorrelated with the IV for the share of migrants (see figure A2). In other words, the instrumented share of high skilled immigrants does not capture the effect of high skilled natives. All in all, we can fairly conclude that omitting the share of skilled natives workers from eq. (1) does not bias the coefficient associated to the instrumented share of immigrants.

Results from the estimation of equation 1 are reported in Tables 5.[28] OLS results are reported in columns (1) as a benchmark, 2SLS estimations in columns (2)-(7), IV-PPML estimator in column (8),[29] and specification with the alternative IV based on extra-France immigrant inflows in column (9). The

[27]It must be noted that the imputed number of immigrant workers in a district is the result of a simple interaction between district- and year-specific variables. See section 5.1 for more details.

[28]Robustness check using techies occupation to define skilled workers are reported in table B1.

[29]The IV-PPML estimator takes into account the count nature of our dependent variable.

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.[30] 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 workers. 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 and/or gentrification) are positively correlated with the patenting activity of districts (Lobo & Strumsky 2008, Carlino & Kerr 2015) but negatively correlated with the settlement of immigrants (Accetturo, Manaresi, Mocetti & Olivieri 2014).[31]

In the bottom part of table 5 we show first stage coefficients and F-stat. The shift-share IV is always relevant (first stage coefficient highly significant) with very reduced weak-instrument concern (F-stat above the rule of thumb of 10). Our results hold also to alternative shift-share IVs definition based on the geographical distribution of immigrants in 1975 and 1990 (see columns 6 and 7). In the last column of Table 5 we use the alternative shift-share IV based on the extra-France inflows of immigrant, and results remain qualitative unchanged. This represents an important robustness check for the causal interpretation of our results. Indeed, removing any French unobserved shock from the shift component of the IV reassures further on the validity of our IV (Borusyak et al. 2021).

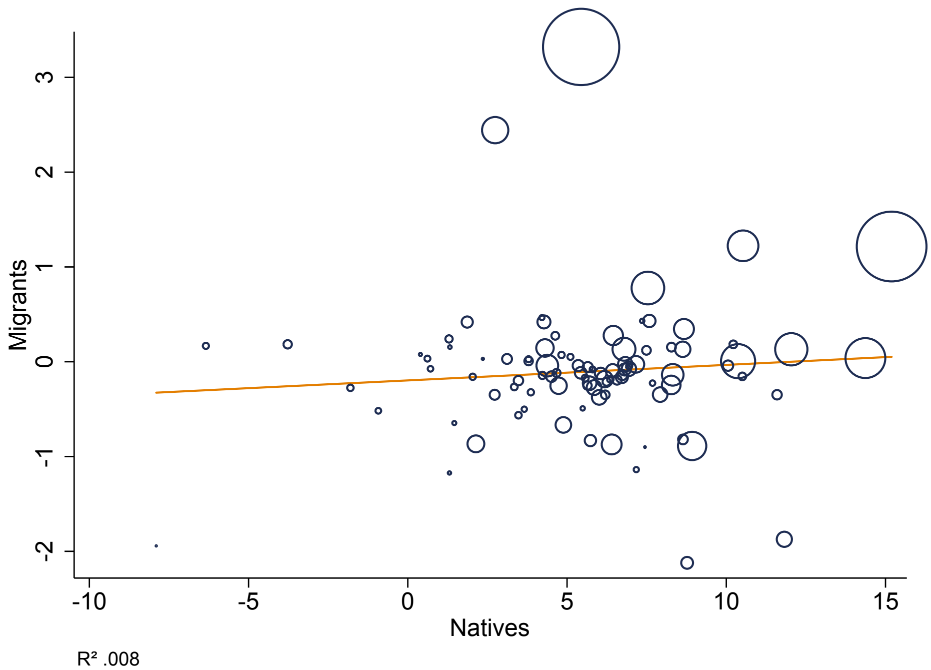
The strong positive effect of skilled immigrant workers on the number of active patents across

[30]We do not control for the total employment of the district to avoid endogeneity concern from internal migration flows.

[31]Accetturo et al. (2014) find that immigration reduces housing price growth in a specific city-district (vis-Гґ-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.

French local labor markets compares with previous studies conducted on US data (Hunt & Gauthier-Loiselle 2010, Burchardi et al. 2020). These studies document the positive effect of skilled immigrant workers on the patenting activity of US states.

Figure 3: Geographical localization of native and immigrant skilled workers across districts. Change in the district's share of native and immigrant skilled workers in the period 1995-2010.



Source: Authors calculations DADS data.

Table 5: Patents and high skilled 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)	(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 (No-France)
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.

In the appendix section B we propose a battery of checks aimed at testing the robustness of our baseline results at district level. We start by showing results when using workers in techies occupation as an alternative proxy for skills, and results do not change (see table B1). In table B2 we use the number of patents *per worker* in the district, and our baseline results hold. Then, in table B3 we report results using 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; and also in this case results hold. In table B4 we show a robustness check using the share of skilled immigrant over total skilled workers as key explanatory variable, and our results hold. In table B5 we adopt a reduced form approach and plug the instrumental variable presented in section 5.1 directly in a OLS estimations. Results from this check are qualitatively unchanged (see table B5). We then propose two specifications in difference (first- and long-difference) to directly test the effect of *changes* in the share of skilled immigrants on *changes* in the patenting activity of French districts. The advantage of the first- and long-difference approach is the possibility of controlling explicitly for pre-trends in the patenting activity of districts, such as the historical changes in the patenting activity of immigrant and native individuals over the XIX^{th} century (subsumed by districts fixed effects in the within specifications). Results from first- and long-difference estimation strongly confirm the robustness of our baseline results.

6.2 Firm-level Evidence

In this sub-section we focus on firms, and take the number of active patents of firm i located in district d at time t as dependent variable. The main explanatory variable $MigSh_{dt}^{High}$ remains at the level of the district because of the highly endogenous hiring process of a specific firm (i.e invalid exclusion restriction for firm-specific shift share IV - see detailed discussion in section 5).[32] Firm-district fixed effects θ_{id} control for any time-invariant characteristics of a specific firm located in a given district.[33] Sector-year fixed effects θ_{st} control for any sector-specific trend in patenting dynamics, and for any time shock (i.e. policy) affecting 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

[32] Table A3 shows the strong positive effect of exogenous district-specific shocks in 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 firms as main explanatory variable (instrumented by our district-specific shift-share IV) and results hold.

[33] If a specific firm changes location over time, the firm-district fixed effects are more accurate than firm fixed effects in controlling for any agglomeration-related factors.

as a proxy for the capital intensity of the firm (in log), and (iii) the total value added of the firm (in log) controlling for the size of the firm.

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

In the vein of what Autor et al. (2020) argue in the context of import competition,[34] the innovation activity of firms may be impacted heterogeneously by a common skilled labor supply shocks; and the effect of skilled immigration may vary with firm characteristics. To explore the heterogeneous effects of skilled immigration on firm patenting, we interact the share of tertiary educated immigrant workers in the district by three metrics based on firm's initial characteristics H_{i,t_0}: (i) productivity (dummy equal to one if firm's productivity at t_0 above 75^{th} percentile); (ii) 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). Being based on the endogenous share of skilled immigrants, also the interaction term $MigSh_{dt}^{High} \times H_{i,t_0}$ has been instrumented by using the shift-share IV discussed above interacted with the firm characteristics H_{i,t_0}.

Results, reported in table 7, clearly show that large, capital intensive and high-productive firms benefit the most from positive shocks in the share of skilled immigrants. In table C2 we replicate the same exercise by using the geographic localization as a firm characteristic. In particular, we explore the heterogeneous effect on the patenting activity of firms based on the district in which the firm is located: (i) Big City (equal to one for Paris, Marseille and Lyon districts), and (ii) historically active district in terms of patenting activity (dummy equal to one if positive patents in the period 1800-1900). The

[34]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. Namely, high productive and capital-intensive firms have smaller reductions in their innovation activity when hit by import competition shocks.

interaction with big city district aims at checking whether our results are driven by cities like Paris, Marseille and Lyon. Results in columns (1) and (3) of table C2 exclude this concern. Interestingly, firms who benefit the most from positive skilled migrants supply shocks are those located in districts with intense historical patenting activity (see columns 2 and 4 in table C2).

The settlement of skilled immigrants across sectors is likely to be persistent over time, and our baseline result can be driven by specific sectors. To address this concern, in figure C1 we show the 2SLS point estimates on the share of skilled immigrants by excluding one sector at time from the estimation sample. Coefficients are all around our baseline 0.047 in table 6 column (2). This strongly suggests that our baseline results do not depend on a specific sector.

Table 6: High skilled migrants and firms' patenting activity. OLS and 2SLS within specification.

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	No-FRA	
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 7: High skilled migrants and firms' patenting activity by type of firm. OLS and 2SLS within specification.

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.

7 Immigration and innovation nexus: The mechanism.

So far we provided robust evidence of a positive (causal) effect of skilled immigration on the innovation (and therefore patenting) activity of French firms. This section aims at clarifying the channel through which the presence of skilled immigrant boost the patenting activity of firms, with a focus on the task-reallocation channel proposed by Peri & Sparber (2009). We start by testing in section 7.1 the robustness of our results to an alternative potential mechanism such as the knowledge diffusion channel discussed in Bahar et al. (2020). Then we theoretically motivate the task-allocation mechanism (section 7.2) and provide empirical evidence of it (section 7.3).

7.1 The role of knowledge diffusion

The diffusion of knowledge conveyed by immigrants at destination uncovered by Bahar et al. (2020) is a plausible explanation for the positive effect of skilled immigration on the patenting activity of districts and firms discussed above. 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 this section we test whether our results are robust to the inclusion of a measure of knowledge diffusion. If so, something else than the diffusion of knowledge by immigrants is at play, and positively affects the innovation activity of firms.

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:

$$\mathrm{KD}_{dt} = \sum_{o} \left[\left(\frac{M_{d,o,1980}}{\sum_{d} M_{d,o,1980}} \right) \times Patents_{ot} \right] \tag{4}$$

where the number of patents delivered by origin-time, $Patents_{ot}$, is allocated across districts based on the geographical distribution of migrants in 1980.[35] 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, reported in Table 8, show a strong effect of knowledge diffusion on the patenting activity of districts (columns 1-3) - confirming the results in Bahar et al. (2020) - and a positive but imprecisely estimated effect on the patenting activity of firms (4-5). Importantly, in both district and firm level evidence the coefficient on the share of tertiary educated immigrants remains strongly significant. This supports the relevance of the *direct* effect of the exposure to positive skilled migrant shocks on the innovation activity of firms on top of the knowledge diffusion channel.

7.2 Immigration, tasks allocation and patenting activity: theoretical motivation

As showed above, the knowledge diffusion is not the only channel through which immigration spurs innovation across (and within) firms. The objective of this section is proposing an alternative mechanism for the migration-innovation nexus in the vein of the tasks re-allocation mechanism in Peri & Sparber

[35] 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.

Table 8: High skilled migrants and firms' patenting activity. The role of knowledge diffusion.

Dep var:	# Active patents in:					
	District			*Firms*		
	(1)	(2)	(3)	(4)	(5)	(6)
High Skill Migrant (sh)	0.100***	0.114***	0.137***	0.046***	0.052***	0.064***
	(0.021)	(0.026)	(0.027)	(0.013)	(0.013)	(0.018)
KD_{dt}	1.742**	1.761**	1.747***	0.029	0.046	-0.030
	(0.725)	(0.738)	(0.747)	(0.218)	(0.218)	(0.225)
Estimator	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
$\mathbf{X}_{dt}$	No	Yes	Yes	No	No	No
$\mathbf{X}_{it}$	No	No	No	No	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	No	No	No
Year Fixed Effects	Yes	Yes	Yes	No	No	No
Firm-District Fixed Effects	No	No	No	Yes	Yes	Yes
Sector-Year Fixed Effects	No	No	No	Yes	Yes	Yes
IV: High Skill Migrant (sh)	Yes	Yes	Yes	Yes	Yes	Yes
Base year IV	1980	1980	1980 (no-FRA)	1980	1980	1980 (no-FRA)
Observations	1,054	1,054	1,054	51,704	51,704	51,704
Cluster	dep	dep	dep	id rt	id rt	id rt
F-stat first stage	15.19	15.13	7.40	249.4	247.7	60.85

Note: Dependent variable is the log of the number of active patents in the district (columns 1-3) and firm (columns 4-6). Standard errors adjusted for clustering by firm and region-year. ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels respectively.

(2009). The basic intuition is that, because of reduced migrants' language/communication skills or to other institutional constraints, skilled immigrants tend to be allocated in technical-intensive and soft-communication tasks (such as in STEM occupations or more broadly in occupations related to pure research requiring technical skills and not a high proficiency in language or communication skills), while skilled natives tend to specialize in language-intensive or administrative/managerial occupations. If immigrant (native) workers are relatively more productive in technical (language) intensive tasks, a positive shock in the skilled migrant labor supply in the district will push firms to hire immigrants and re-allocate tasks to native and immigrant workers based on their relative comparative advantage. This will spur productivity in the innovation activity 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. This brings favorable ground for the allocation of native workers in management oriented positions of the innovation production process; leaving skilled immigrants to purely technical and research oriented positions.

We consider each firm in France in year t producing patenting (i.e. innovation activity)[36] by combining the services of two occupations: (i) purely technical research oriented tasks (T), and (ii) managerial tasks (M).[37] 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). Domestic and foreign-born workers are assumed to be imperfectly substitute in production (within occupation) with elasticity $\rho > 0$ - see Peri & Sparber (2009) and Burstein, Hanson, Tian & Vogel (2020) among others.[38] Each tertiary-educated worker exerts (inelastic) effort such that one-unit of tertiary educated worker of type i (with I, D) produces A_o^i units of service occupation o. As in Burstein et al. (2020), firms combine skilled native and immigrant workers to produce units of each occupation Q_o, according to a CES

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

[37] 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 conclusion hold.

[38] 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.

aggregation:

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

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:

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

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. (6) – 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:[39]

$$\frac{L_o^I}{L_o^D} = \left[\frac{A_o^I}{A_o^D} \right]^{\rho-1} \quad \text{for } o = T, M. \tag{8}$$

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, and define whether it is the technical or the managerial occupation employing relatively more immigrant or native workers:

$$\frac{L_o^I/L_o^D}{L_{o'}^I/L_{o'}^D} = \left[\frac{A_o^I/A_o^D}{A_{o'}^I/A_{o'}^D} \right]^{\rho-1} \tag{9}$$

If immigrant workers have a comparative advantage in occupation o rather than in o', the right side of equation (9) 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

[39] 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):

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

occupation o will be larger than in o'.

Proposition 1 *Firms employ relatively more intensively immigrant workers in occupation where they have comparative advantage with respect to native workers, i.e.* $L_o^I/L_o^D > L_{o'}^I/L_{o'}^D$ *if* $A_o^I/A_o^D > A_{o'}^I/a_{o'}^D$.

If immigrants are relatively more productive than natives in technical tasks (i.e. $A_T^I/A_T^D > A_M^I/A_M^D$) 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 *de facto* excluded by managerial occupations), $A_M^I \simeq 0$ 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 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_o^I/L_o^D) 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.[40]

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.

[40]In the limit case of $A_M^I \simeq 0$ 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.

7.3 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 immigrant in the districts pushes firms to re-allocate tasks across workers (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 9. Second, we test whether the larger availability of tertiary educated immigrants in the district increases the firm's immigrant-to-native ratio in managerial and/or technical tasks (here approximated by PCS occupation codes 47 and 38) - see Table 10. 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 optimal relative immigrant-to-native ratio in technical and managerial tasks, and this to explain the patenting activity of firms - see Table 11.

Table 9 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 shows larger elasticity in switching occupation than immigrants (compare column 1 and 2 in table 9) 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.[41]

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.[42] Accordingly, table 10 shows that an increase in the share of skilled immigrant in the districts pushes French firm to increase the immigrant-to-native ratio in both managerial and technical tasks (see column 2), and the more so in technical occupations (see columns 3-5). This is exactly what our simple theoretical framework predicts.[43] Finally, in Table 11 we show how an

[41]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 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.

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

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

exogenous change in the share of tertiary educated immigrants (shift-share IV) affects the relative immigrant-to-native ratio in technical and managerial tasks (first stage) and how this affects the overall patenting activity of the firms (second stage). The first stage coefficients reported at the bottom of Table 11 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 task across immigrant and native workers implies a boost in the patenting activity of firms.[44] Interestingly, if we simply regress the relative immigrant-to-native ratio in technical and managerial tasks (non instrumented) on the patenting activity of firms (OLS estimation in column 1 of Table E4) we obtain a null coefficient. This supports the validity of our mechanism: only migration-induced shifts in the managerial-to-technical task allocation of native workers (first-stage of the IV approach) have a positive effect on the patenting of firms.

The mechanism discussed so far bases on the implicit assumption that skilled immigrant workers have a *comparative* advantage in purely 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 table E5 we use non-francophone immigrants origins to build our IV. By doing so, the variation in the instrumented share of skilled immigrants does not reflect the variation of francophone origins, and the second stage results do not capture the variation of francophone immigrants that may have comparative advantage in language intensive tasks.[45] Results in table E5 show the robustness of our baseline results to this check.

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).

[44] 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 show 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).

[45] 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 form 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.

Table 9: 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 firms. 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 10: 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)	(5)
High Skill Migrants (sh)	0.042***	0.070***	0.028***		0.026*	
	(0.014)	(0.016)	(0.011)		(0.015)	
Techies Migrants (sh)				0.049**		0.046*
				(0.020)		(0.026)
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-FRA	no-FRA
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***	5.755***	3.294***
F-test first stage	257.5	257.5	257.5	111.5	62.97	57.74

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 column 3). 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 11: 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)	(5)	(6)
$ln\left(\frac{L_T^I/L_T^D}{L_M^I/L_M^D}\right)$	0.008	1.868**	1.766**	1.953**	1.675**	2.289*
	(0.005)	(0.843)	(0.784)	(0.918)	(0.731)	(1.265)
KD			0.294	0.286	0.298	0.271
			(0.611)	(0.668)	(0.584)	(0.769)
Estimator	OLS	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: Task comp.	Yes	Yes	Yes	Yes	Yes	Yes
Base year IV		1980	1980	1975	1990	1980
						no-FRA
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		0.060**	0.064**	0.051**	0.041***	0.161*
F-test		5.95	6.397	5.61	6.78	3.63

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.

8 Conclusions

There are two main aspects of immigration to Europe that we believe have received less attention in policy discussions and academic work, yet they are crucial to understand how immigrants can help Europe: first, the role of (especially low-skilled, young) immigrants in contexts characterized by population aging, such is the case in several European countries (see Börsch-Supan, Leite & Rausch (2019) and Mayda (2019)); second, the impact of skilled migration to Europe, in particular in terms of innovation. In this paper we explore the latter and 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. The innovation effect of skilled migration is not just a scale effect. Skilled migrants have not only increased the number of skilled workers in France. Their positive impact on patenting activity is larger than the corresponding impact of skilled French. We explain this result on the basis of a task specialization story according to which French skilled workers end up specializing in managerial, administrative tasks while foreign skilled workers specialize in technical, research tasks. Gains from specialization of each group of workers in their comparative advantage task explains the increase in innovation.

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A Additional figures and tables

Table A1: 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 A2: 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 A3: District-specific shocks in skilled migrant labor supply and firm's hiring of immigrants.

Dep Var:	Ln(immi$_{it}$ - immi$_{i,t-1}$)		Dummy (immi$_{it}$ > immi$_{i,t-1}$)	
	Panel a: Skilled Immigrants in the firm			
High Skill Migrants (sh)	0.013***	0.035**	0.002	0.007*
	(0.005)	(0.017)	(0.001)	(0.004)
	Panel b: Techies Immigrants in the firm			
High Skill Migrants (sh)	0.014***	0.037**	0.003**	0.011***
	(0.004)	(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	46,771	46,771	46,771	46,771
Cluster	id rt	id rt	id rt	id rt
F-test first stage		243.8		243.8

Note: Dependent variable in columns 1 and 2 is the change in 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: 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

Table A5: 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 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)		

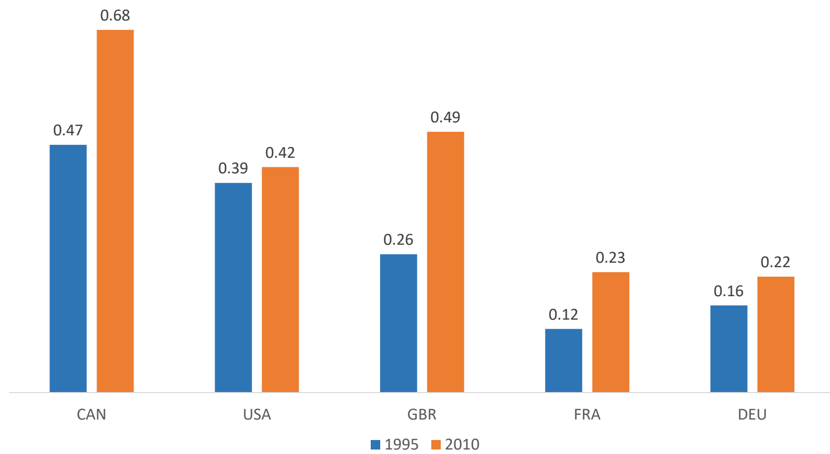
Note: UCI based on γ coefficients from a regression of patents (in log) on the IVs. Clustered standard errors in parenthesis. The number of department for which the instrument is not working is 14 (out of 94). Due to the high number of fixed effects, the boundaries for the firm level specification are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

Table A7: 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:				
$\Delta\ IV_{2010-1995}^{America-Pacific}$	0.729	0.623	-0.224	0.381
	(0.890)	(0.820)	(1.774)	(2.019)
$\Delta\ IV_{2010-1995}^{Africa}$	1.813*	1.659	-1.219	-1.734
	(0.929)	(1.426)	(1.845)	(1.370)
$\Delta\ IV_{2010-1995}^{Europe\&Centr.Asia}$	1.801	2.235	-1.926	-1.329
	(2.228	(2.410)	(3.843)	(3.867)
$\Delta\ IV_{2010-1995}^{Asia}$	0.532	1.056	-0.364	-0.244
	(1.313)	(1.224)	(1.925)	(1.835)
$\Delta\ IV_{2010-1995}^{Europe}$	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

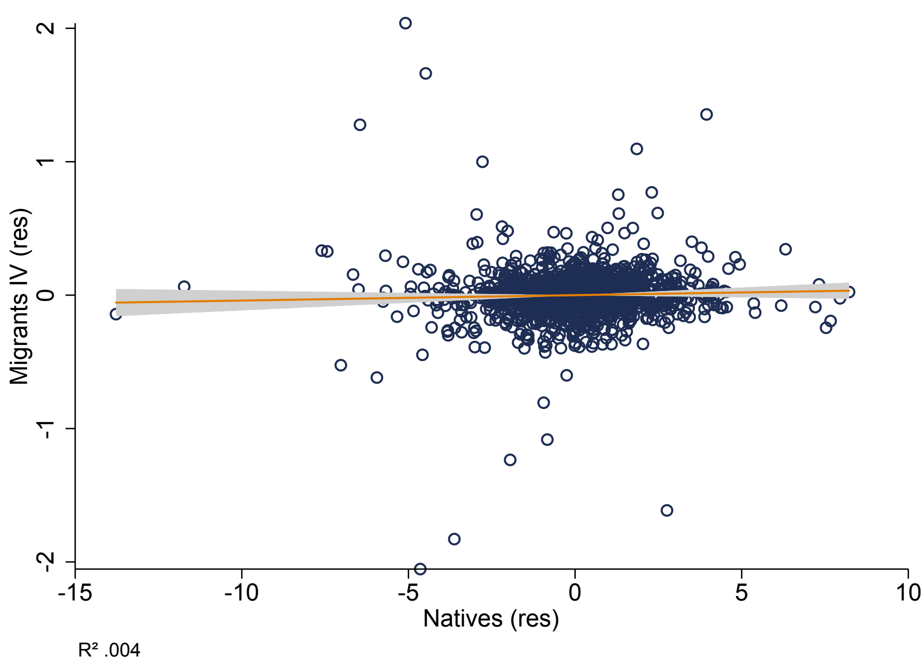
Note: Dependent variable is the log difference in the number of patents in the district over different sub-periods. ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels respectively.

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 collect 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:

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

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 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
							(No-France)
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	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
							(No-France)
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:	# Active patents in the district (ln)			
	(1)	(2)	(3)	(4)
High Skill Migrants (sh)	0.266***	0.268***		
	(0.051)	(0.074)		
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:	# Active patents in the district (ln)			
	(1)	(2)	(3)	(4)
High Skill Migrants (sh)	0.199***	0.204***		
	(0.052)	(0.062)		
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

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)	(3)	(4)
High Skill Migrant (sh)	0.013***	-0.010*	0.066***	0.004
	(0.005)	(0.006)	(0.014)	(0.018)
High Skill Migrant (sh) $\times$ Big City	-0.000		-0.020	
	(0.008)		(0.016)	
High Skill Migrant (sh) $\times$ Mig patenting 800-900 $>$ 0		0.026***		0.046***
		(0.006)		(0.014)
Estimator	OLS	OLS	2SLS	2SLS
$\mathbf{X}_{it}$	Yes	Yes	Yes	Yes
Firm-District Fixed Effects	Yes	Yes	Yes	Yes
Sector-Year Fixed Effects	Yes	Yes	Yes	Yes
IV: High Skill Mig (sh)	No	No	Yes	Yes
Base year IV			1980	1980
Observations	51,704	51,704	51,704	51,704
Cluster	id rt	id rt	id rt	id rt
F-test			59.20	107
Coeff first stage High Skill Mig			3.664***	2.325***
Coeff first stage Interaction			2.351***	4.247***

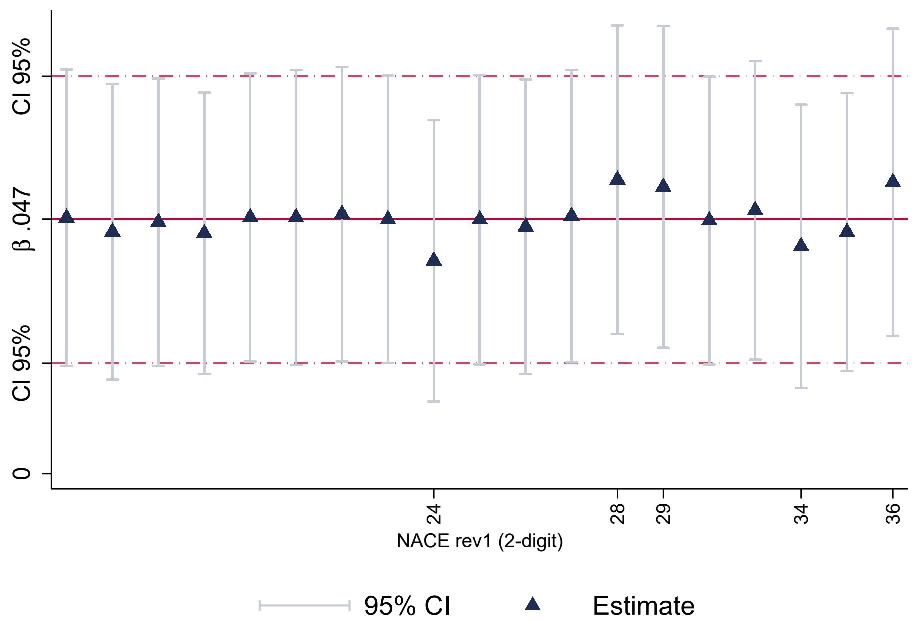
Note: Dependent variable is the log of the number of active patents in the firm. Big cities districts are: Paris, Lyon and Marseilles. Standard errors adjusted for clustering by firm and region-year. ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels respectively.

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

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 7.2. We start by the equation 6 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. $\partial q_o / \partial sh_o = 0$):

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

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

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

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

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 hold by using the share of immigrants over the total employment in occupation o, $L_o^I / \left(L_o^I + L_o^D\right)$, as a proxy for firm's task allocation. Indeed, equation (15) can be re-arranged as

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

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

And finally

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

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. Finally, table E5 shows the robustness of our main results to the exclusion of francophone immigrant workers from the IV.

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)	(6)
High Skill Migrants (sh)	0.020*	-0.009	0.019*	0.018*	0.021*	0.033***
	(0.011)	(0.010)	(0.011)	(0.010)	(0.011)	(0.014)
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	1990	1975	1980 no-FRA
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-test first stage	257.5	257.5	257.5	216.5	271.8	62.97

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)	(5)
Ln(Com/Tech workers)	1.659***	1.702***	1.572***	2.582*	1.949***
	(0.619)	(0.642)	(0.572)	(1.556)	(0.739)
KD				-0.277	-0.071
				(0.911)	(0.614)
Estimator	2SLS	2SLS	2SLS	2SLS	2SLS
$\mathbf{X}_{it}$	No	No	No	Yes	Yes
Firm-District FE	Yes	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes	Yes
IV: Com/Tech workers (ln)	Yes	Yes	Yes	Yes	Yes
Base year IV	1980	1975	1990	1980	1980
					No-FRA
Observations	51,704	51,704	51,704	51,704	51,704
Cluster	id rt	id rt	id rt	id rt	id rt
Coeff first stage	0.061***	0.053**	0.039***	0.039*	0.189**
F-test	6.870	6.700	7.368	2.722	6.458

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 E5: High skilled migrants and firms' patenting activity. Excluding francophone immigrants from the IV.

Dep var:	# Active patents in:			
	District		*Firms*	
	(1)	(2)	(3)	(4)
High Skill Migrant (sh)	0.115***	0.124***	0.047***	0.052***
	(0.023)	(0.026)	(0.014)	(0.013)
Estimator	2SLS	2SLS	2SLS	2SLS
$\mathbf{X}_{dt}$	No	Yes	No	No
$\mathbf{X}_{it}$	No	No	No	Yes
District Fixed Effects	Yes	Yes	No	No
Year Fixed Effects	Yes	Yes	No	No
Firm-District Fixed Effects	No	No	Yes	Yes
Sector-Year Fixed Effects	No	No	Yes	Yes
IV: High Skill Migrant (sh)	Yes	Yes	Yes	Yes
Base year IV	1980	1980	1980	1980
Observations	1,054	1,054	51,704	51,704
Cluster	dep	dep	id rt	id rt
F-stat first stage	13.85	14.35	255.5	254.3
Coeff first stage non-francophone IV	2.400***	2.414***	1.987***	1.983***

Note: Dependent variable is the log of the number of active patents in the district (columns 1-2) and firm (columns 3-4). Standard errors adjusted for clustering by firm and region-year. ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels respectively.