Journal of Economic Geography (2022) **22**, 477–498
Advance Access Publication 3 October 2021

doi: 10.1093/jeg/lbab032

Migration and invention in the Age of Mass Migration

*Dario Diodato**,**, *Andrea Morrison* ***,****,† *and Sergio Petralia****,*****

*CID Growth Lab, Harvard University, 79 JFK Street, Cambridge, MA 02138, USA
**European Commission, Joint Research Centre (JRC), Calle Inca Garcilaso 3, 41092 Seville, Spain
***Department of Management and Technology, ICRIOS-Bocconi University, Via Roentgen 1, 20136 Milano, Italy
****Department of Human Geography and Planning, Utrecht University, Princetonlaan 8A, 3584 CB Utrecht, The Netherlands
*****Department of Economic Geography, London School of Economics, Houghton Street, London WC2A 2AE, UK

†Correspondence to: andrea.morrison@unibocconi.it

Abstract

More than 30 million people migrated to the USA between late-ninetieth and early-twentieth century, and thousands became inventors. Drawing on a novel dataset of immigrant inventors in the USA, we assess the city-level impact of immigrants' patenting and their contribution to the technological specialization of the receiving US regions between 1870 and 1940. Our results show that native inventors benefited from the inventive activity of immigrants. In addition, we show that the knowledge transferred by immigrants gave rise to new and previously not exiting technological fields in the US regions where immigrants moved to.

Keywords: Immigration, innovation, knowledge spill-over, patent, Age of Mass Migration, USA
JEL classifications: F22, J61, O31, R3
Date submitted: 26 February 2020 **Editorial decision:** 7 July 2021 **Date Accepted:** 13 July 2021

1. Introduction

Between 1850 and the mid-1920s more than 30 million people migrated to the USA in search of a better life (Bandiera et al., 2013). The causes and economic impact of this mass migration have received already a good deal of attention in the literature (Hatton and Williamson, 1998). More recently, also due to the backlash against immigration, this topic has regained popularity among scholars, who have initiated a new research line on the economic impact of historical migration in the USA (Rodriguez-Pose and Von Berlepsch, 2014; Abramitzky and Boustan, 2017; Hatton and Ward, 2018; Sequeira et al., 2020; Tabellini, 2020). However, as noted by Abramitzky and Boustan (2017), very few of these works have focused on the link between migration and innovation. This link is an important one though, since many of today's largest US companies (e.g. General Electric) as well as several scientific and technological discoveries can be traced back to foreign born inventors and scientists who entered the USA between late-nineteenth century and 1940s (Hughes, 2004). Some recent evidence for this time period has indeed shown that inventor migrants greatly contributed to the rise of the US inventive activity in specific technological fields (Moser et al., 2014) and in the long-run for the USA as whole (Akcigit et al., 2017). Our work complements these studies by showing that the geographical distribution of immigrant inventors across US regions can explain their technological evolution.

We build a novel dataset of immigrant inventors to examine their impact on the US inventing activity between 1870 and 1940.[1] Did native inventors benefit from immigrants' inventive activity? Did immigrant inventors contribute to develop new technological activities in the regions they migrated to? While these questions have been somewhat addressed by the literature that analyses the effects of present-day immigration on innovation (Kerr et al., 2016; Breschi et al., 2020), there is less systematic evidence of these effects for historical migration in the USA and in particular for the Age of Mass Migration.

Regarding contemporary studies, the literature has provided robust evidence showing that inventive activity as well as scientific outcomes of immigrant workers have been growing steadily in the USA (Kerr, 2007; Hunt, 2011). Findings are instead mixed when it comes to measuring the impact of immigrants' inventive activity on natives (Kerr et al., 2016). Some empirical works highlight the potential crowding-out effect of immigrant scientists (Borjas and Doran, 2012). Others instead show that inventor migrants have no negative effect (Kerr and Lincoln, 2010), or even strong positive effects on incumbents (Hunt and Gauthier-Loiselle, 2010). Other works have turned their attention to role of high-skilled immigrants as carriers of knowledge. For example, Ganguli (2015) shows that Russian scientists who migrated to the USA after the collapse of USSR in 1991 were cited by US scientists more than those who did not migrated, suggesting that migration favoured the transmission of knowledge from origin to destination. More recently, Bahar et al. (2020) conduct a wide cross-country study and show that receiving countries develop comparative advantages in the same technologies of the immigrants' country of origin. This finding suggests that migrants contribute to innovation activity in the receiving countries by 'importing' knowledge from their home country.

Regarding studies that focus on specific historical events in the USA, evidence indicates that migration had positive effects on US inventive activity. For example, Moser et al. (2014) show that German-Jewish chemists escaping Nazi-Germany in the 1930s brought new ideas to the US scientific community that eventually contributed to emergence of new subfields in chemistry. Moser and San (2019) show that the introduction of immigration quotas in USA in the early 1920s had the unintended consequence of reducing the influx of scientists from Europe and overall it led to a sharp decline in US inventive activity in subsequent years. Akcigit et al. (2017) found that the technological fields where immigrants were most active during the Age of Mass Migration developed at faster pace in the long-run (1940–2000).

Our work, by building on the important insights of the above literature, investigates the city-level impact of immigrants' patenting in the period 1870–1940. A major strength of our analysis is that it relies on an original patent dataset that includes the fully disambiguated names of migrant inventors, their country of origin and their county and state of residency in the USA.

1 The Age of Mass Migration usually ends in 1913, with the outburst of WWI, or in the 1920s with the introduction of the national-origins quotas. We extend the time span of our analysis until 1940 because other significant inflows of scientists occurred in this period (e.g. Jews escaping Nazism in Europe in the 1930s) (Moser et al., 2014). Our data also show a robust (albeit declining) patenting activity by immigrants through the 1930s (see Figure 2). The analysis is however robust to the exclusions of the years after 1930 (see Supplementary Tables S.25 and S.26).

We exploit time, place and technological variability in the patenting activity of migrants and natives to test three different channels through which migration may have affected the technological development of places. First, we test the direct impact of immigrant patenting on natives' inventive activity. Second, we use measures of migrants' country-of-origin expertise to evaluate the importance of knowledge diffusion channels. Third, we evaluate how these two channels affect the specialization profile of the places migrants move into and whether new specialization patterns emerge as a result of this.

In order to tackle the first question, the impact of immigrant inventors on US inventive activity, we estimate a baseline model in which we regress the total number of patents by native inventors in a given technology, Metropolitan Statistical Area (MSA), and decade on the number of patents authored by immigrants.[2] To address the endogeneity concerns present in this model, we instrument the number of immigrants' patents with a modified version of the shift–share (Bartik) instrument. We modify the conventional Bartik instrument in three important ways. First, we exclude from the shift component, which is given by the total number of patents in a given year-technology-country of origin, the patents of the immigrant inventors from the corresponding US region in the share component. By doing so we remove the endogenous part of the shift. Second, we use different dimensions to construct the shift and share components, which is usually not the case for the conventional Bartik. While the shift component includes a country-of-origin and technology dimension, the share uses a country-of-origin and region-of-destination dimension. Therefore, the share (which is computed before 1890, while the analysis is carried out from 1900 to 1940) is exogenous because it refers to all inventions of a given country in all technologies, rather than those in a given technology. Third, we replace the share component (i.e. share of patents) with the share of immigrants. The latter two modifications of the instrument should address the critique of Goldsmith-Pinkham et al. (2018) and Jaeger et al. (2018). The instrument is based on the idea that immigrant inventors rely on social-ethnic ties when they have to make a localization choice. This hypothesis finds support in our data, since immigrant inventors do tend to cluster in space in ways that resemble the spatial distribution of immigrants during the Age of Mass Migration (Abramitzky and Boustan, 2017). The estimates of the IV model are positive and significant, with an elasticity of 1.1. By our calculation, this accounts for an additional 20,000 patents. We provide extensive robustness analysis to show that our results are robust to changes in the econometric specification, with particular emphasis to test a dynamic model.

Our second question asks whether immigrant inventors carry knowledge which resembles the technological specialization of their country of origin, thus contributing to the recent literature on knowledge diffusion (Ganguli, 2015; Bahar et al., 2020). To test this mechanism, we adapt to the regional context a measure of 'foreign expertise', which has been first used by Akcigit et al. (2017) for the US case. This indicator is made of two components: the first one captures the technological specialization of the immigrant's country of origin and the second one counts the total number of patents of migrant inventors in a given US region and from a given country of origin (but it does not have a technological class dimension). This measure aims at capturing whether a specific piece of foreign knowledge is imported by an inventor from her country to the US city she moved to. Our results show that inventor migrants bring with them foreign expertise that becomes relevant for the technological development of the places they migrate to.

2 We use the 2010 standard for delineating MSAs.

Finally, we test whether immigrant inventors contribute to shape the technological evolution of the receiving region. We observe that new technologies, which were not present yet in a region, emerged because of the inventive activity of immigrant inventors in those regions. Our results suggest that both immigrants' inventive activity and the knowledge they imported from their home country helped US cites to enter new technological fields. However, we present suggestive evidence indicating that migrants influence US innovation primarily through their own knowledge spilling over to US inventors, rather than by connecting them to foreign knowledge.

Our findings are in line with a growing literature that analyses the role high-skilled immigrants in the host country (Kerr et al., 2016; Breschi et al., 2020). Our work also contributes to the recent literature on historical migration in the USA (Rodriguez-Pose and Von Berlepsch, 2014; Sequeira et al., 2020; Tabellini, 2020). More specifically, we add original evidence to the strands of studies that focused on the link between historical migration and innovation in the USA (Moser et al., 2014; Akcigit et al., 2017; Moser and San, 2019). In line with these studies we find that immigrant inventors played a crucial role in the construction of the US technological system in the late nineteen and early twentieth centuries.

We complement the above literature in two ways. First, our work generalize some of the important findings of these studies that focused on specific historical cases (e.g. Moser et al. (2014) on German chemists; Ganguli (2015) on Russian scientists) by looking at a broader set of immigrant groups and technological fields. Second, our work adds a geographical dimension to the studies that had mainly a country perspective (Akcigit et al., 2017; Moser and San, 2019) and shows that immigration played an important role also at local level.

The paper is structured as follows. In Section 2, we present some historical background information about the Age of Mass Migration and invention in the USA. We illustrate how immigrants related to invention and patenting in the USA. In Section 3, the data are presented with a description of how we built the dataset. Section 4 lays out our empirical strategy, while Section 5 illustrates the main findings. Section 6 concludes with some discussion of the contribution of our work and its possible extensions.

2. The Age of Mass Migration in the USA: immigration, invention and patenting

More than 30 million people migrated to the USA from all around the world between the 1830s and 1920s (Hatton and Williamson, 1998). A large majority consisted of Europeans from different geographical origins who entered USA in large consecutive waves. The Age of Mass Migration came to an end when in 1924 the US Congress passed a law that introduced country-specific quotas (Goldin, 1994).

Along with the millions of low-skilled immigrants entering the USA during these six decades, in the order of thousands were or became inventors and patentees (Khan, 2005; Akcigit et al., 2017). Although it may appear at first surprising, this is less so if one considers that in the late nineteenth century in the US inventive activity was primarily an individual endeavor, which required relatively little capital (Hughes, 2004) and formal training. Inventions were often the outcome of a trial and error process and fortunate accidents which allowed to come up with smart solutions that fixed specific technical problems (Sokoloff, 1988; Khan, 2005).

Another important aspect to take into account is that the US patent system, in contrast to the British or French ones, had very low barriers to entry: registering a patent was relatively cheap and technological invention was strongly promoted and enforced. An additional feature of the US patent system favoured particularly the participation of disadvantageous groups, including immigrants, as it required that a patent should be granted to the true and first inventor worldwide, which contrasted with England and other European countries, where a patent was granted also to imported foreign inventions. This latter practice clearly favoured wealthy traders and companies who could afford purchasing technology abroad and patent them domestically (Sokoloff, 1988). All the above has led Khan (2005) to state 'that the notion of patenting and inventive activity as means of achieving eminence, especially for disadvantage groups, is borne out by the experience of foreign-born inventors' (p. 2014).

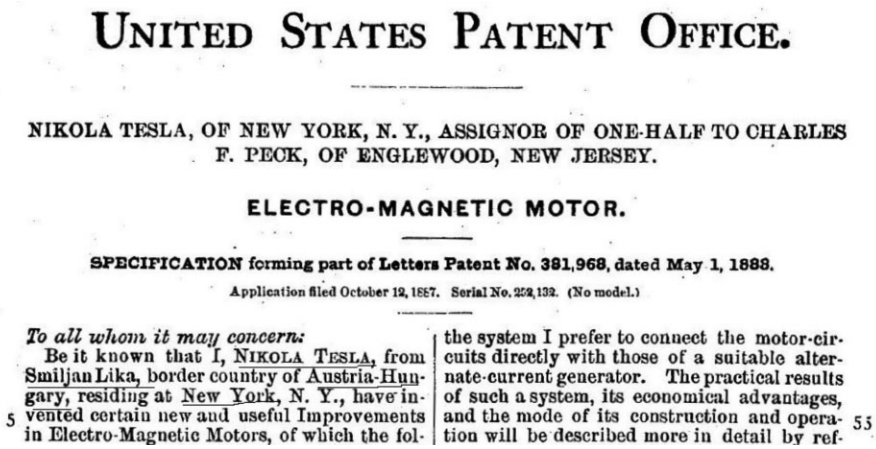
The biographies and background of immigrant inventors are however very heterogeneous. We could classify them in two broad categories. A first group includes those who arrived to the USA during their childhood, like Elihu Thomson, prolific inventor and founding father of successful companies (e.g. General Electric, Thomson SA). A second category refers to foreign-born inventors who were already trained or active in a specific scientific field before moving to the USA. Tesla is perhaps the most well-known example in this group, with his experience and training earned in Europe, he soon built a reputation of prolific inventor in the USA (Hughes, 2004; Tesla, 2011).

3. Identification of immigrant inventors in patents

Since we focus on the impact of particular type of immigrants, that is those who arrived in the USA with a baggage of relevant working or intellectual experience, most of the available databases and empirical approaches that are common in the literature are not a suitable option. This is because they usually identify migrants without distinguishing where they acquired their knowledge. For instance, when migrants are identified using the ethnic origin of their surnames it is not possible to know whether they arrived to the USA during their childhood and were therefore trained and raised in the USA. In this section, we describe the construction of a new dataset that identifies migrants in historical patent documents at the USPTO. We exploit the fact that old historical patent documents, prior the 1940s, include information about the nationality of the inventors by disclosing the place they come from if they are foreign. Consider for instance Figure 1, which shows patent document number 381,968 granted to Tesla,[3] who arrived to the USA in 1884 from Europe and started working at Edison's Company almost immediately after. Note that patent documents were describing not only the place of residence of the inventor (New York) but also its nationality (Austro-Hungarian).

The creation of this database can be divided into three distinct stages. The first challenge consisted in identifying historical patent documents of migrants inventors from the pool of all patented inventions granted at the USPTO prior the 1940s. Since manually scanning all documents for foreign inventors would render the task unfeasible, we relied instead on an automated algorithm to identify potential candidates. We trained an algorithm to identify patents who could be attributed to an immigrant inventor based on the

3 See entire patent document here: https://patents.google.com/patent/US381968.



UNITED STATES PATENT OFFICE.

NIKOLA TESLA, OF NEW YORK, N. Y., ASSIGNOR OF ONE-HALF TO CHARLES F. PECK, OF ENGLEWOOD, NEW JERSEY.

ELECTRO-MAGNETIC MOTOR.

SPECIFICATION forming part of Letters Patent No. 381,968, dated May 1, 1888.

Application filed October 12, 1887. Serial No. 252,132. (No model.)

To all whom it may concern:

Be it known that I, NIKOLA TESLA, from Smiljan Lika, border country of Austria-Hungary, residing at New York, N. Y., have invented certain new and useful Improvements in Electro-Magnetic Motors, of which the fol-

the system I prefer to connect the motor-circuits directly with those of a suitable alternate-current generator. The practical results of such a system, its economical advantages, and the mode of its construction and operation will be described more in detail by ref-

Figure 1. Nationality information contained in historical patent documents.

vocabulary used in its description. Words such 'a subject of', 'a citizen of' or 'kingdom' are usually associated with the description of the location of foreign inventors in patents. These should appear in combination with words such as 'residing in' and the name of an US location. This algorithm is analogous to the one described and documented in Petralia et al. (2016) but tailored to this particular problem.[4]

It is likely, however, that the subset of patents identified as coming from migrants (as well as the information extracted from them) contains mistakes. This could happen if a certain combination of keywords results in our algorithm identifying the presence of a migrant when it is actually not the case. For instance, the word 'England' may refer to the location of the inventor ('New England') instead of his nationality, thus increasing the probability of falsely identifying the presence of a migrant in the patent. The second step of the procedure consisted on correcting possible mistakes made by the algorithm. To do so we manually checked all patents that were flagged as produced by an immigrant inventor (approximately 36,000) and whenever necessary we corrected misspells or added the missing information. From this procedure, we obtained 15,055 manually checked patent–inventor observations.[5]

Finally, we had to correct for the fact that our automated detection algorithm would not detect the patents of immigrants that have obtained the US citizenship after residing in the USA for some time. This is because foreign citizenship was not disclosed in patent documents if the immigrant had obtained the US citizenship. We tackled this issue by

4 See https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/3ZLC8E, for a detailed example.

5 Note that since our procedure to retrieve migrant inventors involves several steps, we are taking a different approach than what is customary to deal with the trade-off between the type I and type II errors. If the procedure would have only one step, meaning that the patents we flag in this first step will be the ones that we will use in the estimations, we would be mostly focused on balancing the type I and type II errors, as in Petralia et al. (2016). However, we devised a procedure that contains several steps, where some of them include the possibility to manually correct errors. Since in the second step we can correct (delete) false positives, our strategy was to choose an unusually low threshold to include as many potential candidates as possible, thus minimizing the probability of leaving a migrant out.

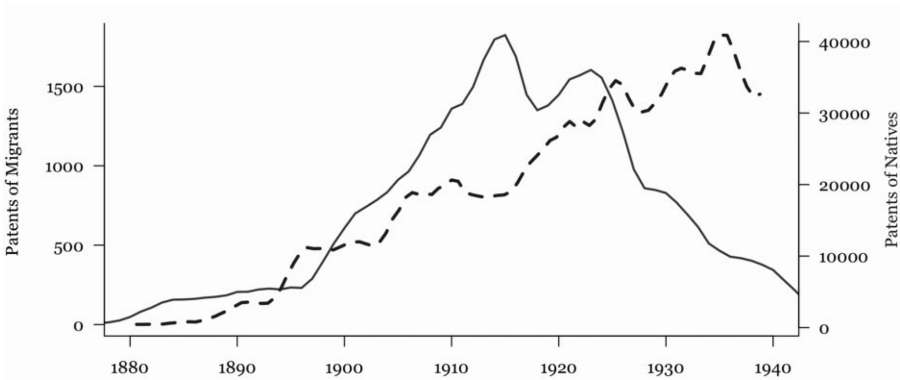


Figure 2. Migrant and native patenting over the period.
Notes: Migrant patenting is marked with the solid blue line and it is read on the left scale. Patents of natives with the dashed red line on the right scale.

text-mining all patents documents in the period 1840–1940 to search for the names of the 15,055 manually identified migrants.[6]

We allowed for minor discrepancies in the name matching algorithm to take into account the possibility of minor misspellings, which were later manually checked. This resulted in a final database containing 49,841 manually checked inventor–patent combinations with information about the place of residence of the inventor, the country of origin, the year the patent was granted and the technological profile of the patent. Even though we manually checked that all matches were not due to misspells, it could be the case that some of the additional patents found at this stage are not of the migrant inventor in question but from somebody else with the exact same name. We applied several criteria to restrict this possibility. If we include all inventors that match the originally manually collected name we obtain the 49,841 inventor–patent combinations we mentioned before. If we restrict to name matches that occur within a 20-year window from the original (manually identified) name this number goes down to 47,186 and to 40,582 if we use a 10-year window instead. In addition, we restrict to name matches for which the state of residence also matches within a 20- or 10-year window, which results on a sample of 36,414 and 33,209 inventor–patent combinations, respectively. Our results are robust to these different matching approaches.

Figure 2 shows the total number of patents of immigrant and native inventors during the period. We observe a growing trend in immigrant patenting which peaks in 1916, possibly capturing the effect of WWI on both patenting activity and inflow of migrants. After that, a new peak is reached in 1926, right after the introduction of immigration quotas, which ended the open door immigration policy in the USA.[7] This time dynamics follows closely the inflow of migrants during that period of time (Gibson and Lennon, 1999). On the other hand, the patenting activity of natives shows a clear sustained increased in the period considered.

6 Once we identify the additional patents of the manually identified immigrants in the dataset, we consider them as made by immigrant inventors.
7 This pattern is similar across nationalities, in the Online Appendix we show it for the most prolific ones (Supplementary Figure S.1).

Table 1. Patents by nationality

Origin	Patents	Share
Great Britain and Ireland	18,093	0.368
Germany	6430	0.131
Sweden–Norway	6092	0.124
Austria–Hungary	3569	0.073
Russia	3290	0.067
Italy	2461	0.050
Canada	2081	0.042
Switzerland	1489	0.030
Denmark	1147	0.023
France	1136	0.023
Others	3408	0.069

Table 1 shows the most prolific nationalities. Not surprisingly, this ranking resembles to a large extent the distribution of the immigrant population in the USA, with Great Britain and Ireland at the top of the list, followed by Germany (Gibson and Lennon, 1999). All major European countries which had large flow of emigrants to USA are listed, that is Sweden, Italy, Russia and central European countries. We have grouped countries following the USPTO aggregation criteria. More specifically, Great Britain and Ireland includes Ireland, Wales, Scotland and England, Austria–Hungary includes Austria, Hungary, Croatia, Czechia, Slovakia and Slovenia, while Russia includes also Lithuania and Latvia. This is because the USPTO referred to these territories exchangeably, sometimes referring to cities like Vienna as part of Austria and others as part of the Austro-Hungarian empire.

Turning to the geography of these migrant inventors, Figure 3 compares the spatial distribution of patenting and non-patenting (from census records) migrants. Both maps show the most popular migrant group per county, using the patenting activity of migrants (a) and the total population (b). Migrant inventors tended to cluster in space resembling closely the geographical footprint of other migrants from the same nationality (Abramitzky and Boustan, 2017). Not surprisingly, large urban areas are highly represented, with cities like New York and Chicago ranking at the top. Even though the east coast is the epicentre of migrant inventive activities (and patenting in general), large communities of German and Scandinavian immigrants were active throughout the Mid-West.

Finally, in Table A1 in the Appendix, we show the technological composition of migrants' (and US natives) patenting activity in the period. We note that German inventors were relatively more oriented to the production of Mechanical and Electrical & Electronic technologies than US natives. In addition, North-Europeans and Russians were relatively more predominant than US natives in Electrical & Electronic, one of the fastest growing technological domains of the time (Hughes, 2004). We highlight that, for our dataset, the classification of patents into technologies relies on the United States Patent Classification (USPC). See more details in the notes to Table A1.

4. Empirical strategy

4.1. Impact on the inventive activity of US regions

In order to investigate the contribution of immigrant inventors to the inventive activity of US regions, we estimate the following model:

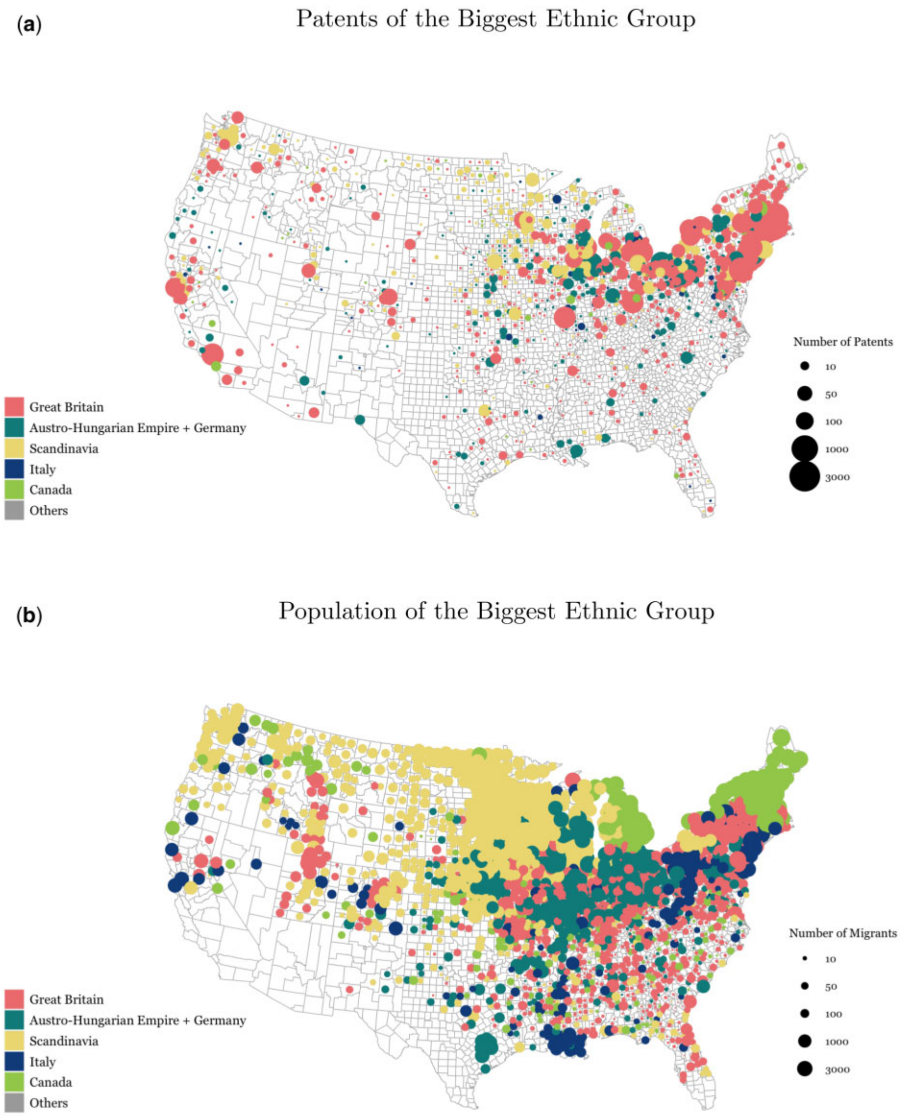


Figure 3. Spatial distribution of migrants. (a) Patents of the biggest ethnic group. (b) Population of the biggest ethnic group.

$$\mathrm{nat}_t^{rk} = \beta_1 \mathrm{mig}_t^{rk} + \gamma_t^r + \psi_t^k + \varphi^{rk} + \eta_t^{rk}, \tag{1}$$

where nat_t^{rk} is the total number of patents (in logs[8]) by native inventors in technology k, region r and period t. Note that in the benchmark regressions, we use MSAs and 10-year

8 In the benchmark regressions we keep all observations, including region–technology combinations with zero patenting. We, thus, measure the log of patent count as $\log(\text{patents} + 1)$. We test the robustness of this choice in several ways, including by dropping all observations with zeros (see Supplementary Tables S.7–S.12 and the discussion in the Online Appendix). We find that results are consistent.

windows, for region and period, respectively. Our variable of interest, mig_t^{rk}, is the log of the number of patents authored by immigrants. Lastly, γ_t^r, ψ_t^k, φ^{rk} and η_t^{rk} are the three interaction dummies and the error term. Note that γ_t^r captures all the region-level variables such as value added, population, population density (etc.), ψ_t^k controls for the state of the technology and φ^{rk} for the (time-invariant) technological specialization of the region.

This basic empirical setup, as described in Equation (1) is highly endogenous—even though the model is saturated with all possible dummies. In fact, idiosyncratic changes in the conditions of a region-technology combination (for instance, the opening of a research laboratory by a corporation or a university) would affect both nat_t^{rk} and mig_t^{rk} and bias the estimate of β_1. For this reason, in the next section, we describe how we identify the impact of migrants on regional innovation in the USA.

4.2. Identification

We deal with the inherent endogeneity of the empirical model in Equation (1) in two ways: first, we instrument mig_t^{rk} using a modified version of a shift–share (Bartik) instrument and, second, we exploit the panel nature of our data to re-write Equation (1) into a dynamic empirical model.

4.2.1. Shift–share instrument

Shift–share instruments are well grounded in the migration literature (see Card, 2001) and widely applied in the recent literature on immigration and innovation (see Hunt and Gauthier-Loiselle, 2010; Ganguli, 2015). The instrument is usually composed of two parts: the inflow of immigrants from a given country to a destination country (e.g. the shift) and the share of immigrants of that country residing in a specific city in the previous period (e.g. the share). In our case, the instrumental variable is constructed as follows:

$$\mathrm{IV}_t^{rk} := \sum_c \frac{\mathrm{MIG}_{t_0}^{cr}}{\mathrm{MIG}_{t_0}^{c}} (\mathrm{MIG}_t^{ck} - \mathrm{MIG}_t^{crk}), \tag{2}$$

where MIG is the non-log version of the endogenous variable ($\log(\mathrm{MIG}_t^{crk}) = \mathrm{mig}_t^{crk}$). The shift component of the instrument ($\mathrm{MIG}_t^{ck} - \mathrm{MIG}_t^{crk}$) is the total flow of patents in period t, from an immigrant born in country c, in technology k. Note that, however, this total flow excludes those patents in region r (MIG_t^{crk}) to remove the endogenous portion of the shift. We further highlight, in fact, that in our setting we have an additional dimension (i.e. technological class k), which is typically not available to most studies on migration using shift–share instruments. We can therefore exploit this feature in the construction of the instrument: while for the shift we use the flow with country-of-origin × technology dimension, for the share we use country-of-origin × region-of-destination. This share (which is computed with $t_0 < 1890$, when the analysis is carried out from 1900 to 1950) is exogenous because it does not contain migrants in technological class k specifically, but inventions from country c in all technological classes.

This should address the critique of Goldsmith-Pinkham et al. (2018) or Jaeger et al. (2018) who point out that the share component of the instrument is generally problematic, as adjustments from previous migration may still be ongoing. Here, we suggest that the next wave of migrants with specialization in technology k would migrate where there are existing communities of fellow countrymen, because of social ties, hence irrespective of technological specialization of the previous wave. The ongoing adjustments should be exogenous to the competence brought by the migrant in technology k.

To go a step further, for our benchmark results, we substitute the share of patents by migrants in Equation (2) with the share of all migrants from country c (inventors and non-inventors) from the population census of 1890.[9]

$$\tilde{\mathrm{IV}}_t^{rk} := \sum_c \frac{\mathrm{CENSUS}_{t_0}^{cr}}{\mathrm{CENSUS}_{t_0}^{c}} (\mathrm{MIG}_t^{ck} - \mathrm{MIG}_t^{crk}). \tag{3}$$

Hereafter, we denote the log of the IV variables as iv_t^{rk} and $\tilde{\mathrm{iv}}_t^{rk}$, respectively.

4.2.2. Dynamic model

As a complementary identification strategy, we also attempt to account for potential endogeneity of nat_t^{rk} and mig_t^{rk} with a dynamic empirical model. We re-write Equation (1), as

$$\Delta \mathrm{nat}_{t-1\to t}^{rk} = \theta \mathrm{nat}_{t-1}^{rk} + \beta_1 \mathrm{mig}_{t-1}^{rk} + \gamma_t^r + \psi_t^k + \eta_t^{rk}. \tag{4}$$

That is, we now relate the growth (log difference) in patenting activities of natives to patents of migrants in the previous period. Crucially, we also include a lagged dependent variable so that changes in the environment (shocks in η_t^{rk}) affecting both native and migrant patenting are absorbed by nat_{t-1}^{rk}. In addition, we instrument mig_{t-1}^{rk} with $\tilde{\mathrm{iv}}_{t-1}^{rk}$.

We finally note that in the dynamic setting we cannot include region × technology dummies (φ^{rk}) without biasing the results (Nickell bias).[10] This may raise the concern that (although we cluster standard errors by region and technology) modest temporal variation may inflate significance without fixed effects. We, then, additionally estimate the model using DIFF-GMM (Arellano and Bond, 1991) and—as a further check—we re-design the dynamic model to exploit the whole time-span of our data, but in cross-sectional form:

$$\Delta \mathrm{nat}_{t_1\to t_2}^{rk} = \theta \mathrm{nat}_{t_1}^{rk} + \beta_1 \mathrm{mig}_{t_1}^{rk} + \delta^r + \iota^k + \eta^{rk}, \tag{5}$$

where $t_1 = [1890, 1930)$ and $t_2 = [1930, 1950)$. The corresponding instruments also use $t_1 = [1890, 1930)$ for the shift and, as before, $t_0 = [1870, 1890)$[11] for the share.

5. Empirical results

5.1. Impact on the inventive activity of US regions

Our original dataset exploits region × technology × time variation and is organized—for the purpose of the benchmark empirical analysis—into 366 MSAs, 417 USPC classes and 5 10-year windows, for a total of 763,110 observations. In 19% of these observations, we record at least one patent. Descriptive statistics of the dataset can be found in Table A2.

9 When we use patents data for the share, we sum all the patents published by migrants from 1870 to 1890. This is because patent production is a flow variable. When we compute the share using census data on migrants, we use the stock of foreign born in 1890 instead.

10 For completeness, we will report these results nonetheless.

11 $t_0 = 1890$ for $\tilde{\mathrm{iv}}_{t_1}^{rk}$.

Table 2. The relationship between US and immigrant patenting

Dependent variable: Patents of natives	OLS (1)	OLS (2)	OLS (3)	OLS (4)	IV (5)	IV (6)
Patents of migrants	2.887***	1.082***	0.140***	0.275***	6.135***	1.079***
	(0.145)	(0.139)	(0.049)	(0.028)	(1.640)	(0.264)
Adjusted R^2	0.118	0.555	0.764	0.791		
Observation	763,110	763,110	763,110	763,110	763,110	763,110
F (first stage)					34.063	50.401
Dummies	t	k, r, t	kr, t	kr, kt, rt	t	kr, kt, rt

****Notes:* All variables are in logs. Dependent variable: number of patents by natives (nat_t^{rk}). Explanatory variable: patenting activity by migrants (mig_t^{rk}). Instrumental variable: $\widetilde{\text{iv}}_t^{rk}$. Cities (MSAs) are used for the regional dimension, while USPC for technology. City and technology cluster robust standard errors in parentheses. Time t is in decades. First-stage relevance reported with Kleibergen–Paap F-statistic. Significance is denoted with ***$P < 0.01$, **$P < 0.05$, *$P < 0.1$.

In Table 2, we report the results of estimating Equation (1). This is the most basic setup we estimate, where we simply relate contemporaneous patents of natives to patents of migrants.

In Columns 1–4, we estimate the model with OLS and various combination of dummies. The most complete estimation (with all interacted dummies) in Column (4) suggests an elasticity of about 0.2. As discussed in Section 4.2, the OLS estimate of the contemporaneous model is likely to be biased by endogeneity. Columns (5) and (6) report the instrumental variable estimates of the model in Equation (1).[12] The shift–share instrument ($\widetilde{\text{iv}}_t^{rk}$) uses past population by country of origin for its share component, as described in Equation (3). The Kleibergen–Paap F-statistics are well-above the usual cut-off point of 10.[13]

The IV estimate (with an elasticity of about 1 in Column 6) is significantly larger than the corresponding OLS estimate.

A few observations are in order: first, to get a sense of the magnitude of this coefficient we note that the standard deviation of mig_t^{rk} is about 0.097 (roughly one migrant), meaning that one s.d. increase brings about $1.079 \times 0.097 = 10.46\%$ growth in local patents. While smaller than other estimates in literature, such as Burchardi et al. (2020), that is still rather large: about 20,000 patents in total.[14]

Second, comparing OLS estimate with IV we note that, while an upwards bias is what we expected, we find (in line with similar studies on this topic, such as Hunt and Gauthier-Loiselle, 2010; Moser et al., 2014; Ganguli, 2015) the opposite. The most likely explanation for an IV estimate larger than the OLS is that the IV corrects for measurement

12 See Supplementary Table S.29 for the first stage.

13 Lee et al. (2020) recently argue that using a fixed threshold for F is misleading. Following their table of critical values for Column (6): with $\sqrt{F} = 7.1$, the critical value in the second stage for 5% significance is 2.15, almost half of the second stage t-ratio of 4.087, which we observe in Column (6).

14 One SD increase brings 40,000 new patents per decade. An increase from zero to the mean brings 20,000 patents in total.

Table 3. The relationship between US and immigrant patenting: alternative specification

Dependent variable: Patents of natives (growth between $t-1$ and t)	OLS (1)	OLS (2)	OLS (3)	OLS (4)	IV (5)	IV (6)
Patents of natives ($t-1$)	−0.188***	−0.394***	−0.978***	−0.390***	−0.237***	−0.422***
	(0.019)	(0.019)	(0.019)	(0.020)	(0.028)	(0.024)
Patents of migrants ($t-1$)	0.603***	0.428***	0.178***	0.403***	1.566***	1.267***
	(0.048)	(0.046)	(0.016)	(0.039)	(0.541)	(0.469)
Adjusted R^2	0.088	0.207	0.389	0.237		
Observation	610,488	610,488	610,488	610,488	610,488	610,488
F (first stage)					27.407	41.320
Dummies	t	k, r, t	kr, t	kt, rt	t	kt, rt

Notes: All variables are in logs. Dependent variable: growth of patenting activity by natives ($\Delta \text{nat}^{rk}_{t-1 \to t}$). Explanatory variables: patenting activity by natives (nat^{rk}_{t-1}) and migrants (mig^{rk}_{t-1}). Instrumental variable: $\text{iv}^{\widetilde{rk}}_{t-1}$. Cities (MSAs) are used for the regional dimension, while USPC for technology. City and technology cluster robust standard errors in parentheses. Time t is in decades. First-stage relevance reported with Kleibergen–Paap F-statistic. Significance is denoted with $^{***}P < 0.01$, $^{**}P < 0.05$, $^{*}P < 0.1$.

error. However, there are also reasons to believe OLS underestimates the coefficient. For instance, inventor migrants may have faced high entry barriers to the US local labour market. So, they would not have been able to pick their preferred occupation/location, but rather they ended up in more marginal jobs and/or peripheral areas, where they faced less competition from natives; another possible explanation, following the argument already made by Ganguli (2015), is that a downwards bias occurs when immigrants arrive to specific places with a job offer already. If this is the case, we can assume they move to a place where their skills and main field of activity is already well-known and related to the one of the employer. The potential for knowledge spillover is then limited. Instead, the IV allocates these immigrants based on their social networks (co-ethnicity), so to places where their field of activity is possibly unknown, therefore their impact in terms of knowledge spillovers is most likely to be higher.

Lastly, we observe that (as we show in the reminder of this section) this magnitude is remarkably robust across specifications, suggesting that a large role was played by migrants in the innovation environment of the USA of the early 20th century.

In Section 4.2, we propose an alternative econometric specification that could better control for the simultaneity of nat^{rk}_t and mig^{rk}_t (see Equation 4). Table 3 reports the coefficients estimated using this dynamic setting. The benchmark results for Table 3 are Columns (4) and (6) for OLS and IV, respectively. The estimated coefficients in these cases are in line with those reported in Table 2. Note that, unlike in Table 3, Columns (4) and (6) in this table do not include city × technology dummies. This is to avoid introducing Nickell bias, which is indeed present in Column (3) and, to a lesser extent in Column (2).[15]

15 A standard alternative strategy to estimate a FE model in dynamic setting is to use an Arellano–Bond style estimator. In Supplementary Table S.13, we show that results are robust when the dynamic model is estimated via DIFF-GMM.

The final specification we discuss for this section is the one reported in Equation (5). Similarly to the growth-level setup, whose estimates are reported in Table 3, this empirical model differs in that we aggregate the whole dataset in three time periods ($t_0 = [1870, 1890)$, $t_1 = [1890, 1930)$, $t_2 = [1930, 1950)$). As we use t_0 for the instrument, t_1 for the level variables and the difference between t_2 and t_1 for the growth variables, we functionally have a cross-sectional dynamic model. The results of this exercise are reported in Supplementary Table S.1. Coefficients are in line with previous estimates, even though the most complete IV estimate (Column 4) suggests a smaller elasticity of about 0.7.

5.2. Impact of foreign expertise on the inventive activity of US regions

The empirical findings in the previous section indicate that the knowledge of the migrant plays a strong role stimulating innovation in the USA. This knowledge is likely to have originated in the migrants' country of origin, since foreign born who lived for long (and possibly studied) in the USA become citizen, and thus are not picked up as migrants by our algorithm.

In line with a growing literature on contemporary immigration and knowledge diffusion (Miguelez and Temgoua, 2019; Bahar et al., 2020), our analysis suggests that migrants acted as carriers of knowledge across distant places. However, our measurement of knowledge flow from migrants (mig_t^{rk}) leaves an important question open: are inventor migrants bringing their own knowledge or are they also acting as a bridge between their country of origin and their region of destination in the USA?

We introduce here a variable that can help make the distinction. We take this variable from Akcigit et al. (2017), but adapt it to our regional context: E_t^{rk} is the foreign expertise on technology k that migrants bring to region r.

$$E_{t_1}^{rk} := \sum_c \frac{\mathrm{PAT}_{t_0}^{ck}}{\mathrm{PAT}_{t_0}^{c}} (\mathrm{MIG}_{t_1}^{cr} - \mathrm{MIG}_{t_1}^{crk}), \tag{6}$$

where $\mathrm{PAT}_{t_0}^{ck}$ is the production of patents of country c in technology k *at home*.[16] ($\mathrm{MIG}_{t_1}^{cr} - \mathrm{MIG}_{t_1}^{crk}$) is the flow of patents by migrant inventors from country c, in region r (excluding those in the target technology k).

This indicator of expertise, which differs from the one proposed by Akcigit et al. (2017) because it varies also by region r, is similar in spirit to our instrumental variable (Equations 2 and 3). This measure of expertise inverts the indices r and k for the share and the shift components (apart from using inventions by non-migrants in the share component). While this may appear minor at first sight, it is substantial: controlling for mig^{rk} or $\tilde{\mathrm{iv}}^{rk}$, expertise captures the connections US cities have with technology k to countries that are specialized in that technology, *beyond having experts that migrated from those countries*. In this way, we can distinguish between the knowledge that was brought *directly* by migrants through their own competence and the knowledge brought *indirectly* through links with the home country.

The specification estimated by Akcigit et al. (2017) is comparable to our model in Equation (5). We then write:

16 This data come from the HistPat International dataset (Petralia, 2019), available at: https://doi.org/10.7910/DVN/QT4OJS.

Table 4. The role of expertise in innovation

Dependent variable: Patents of natives (growth between t_1 and t_2)				
	OLS (1)	OLS (2)	IV (3)	IV (4)
Patents of natives (t_1)	−0.394***	−0.525***	−0.409***	−0.541***
	(0.023)	(0.018)	(0.029)	(0.022)
Patents of migrants (t_1)	0.316***	0.278***	0.731**	0.618**
	(0.050)	(0.047)	(0.287)	(0.245)
Expertise (t_1)	0.852***	0.317***	0.579***	0.145*
	(0.166)	(0.111)	(0.178)	(0.084)
Adjusted R^2	0.265	0.435		
Observation	150,426	150,426	150,426	150,426
F (first stage)			37.626	64.128
Dummies		k, r		k, r

Notes: All variables are in logs. Dependent variable: growth of patenting activity by natives ($\Delta \mathrm{nat}^{rk}_{t_1 \to t_2}$). Explanatory variables: patenting activity by natives ($\mathrm{nat}^{rk}_{t_1}$) and migrants ($\mathrm{mig}^{rk}_{t_1}$), and expertise ($e^{rk}_{t_1}$). Instrumental variable (for $\mathrm{mig}^{rk}_{t_1}$): $\tilde{\mathrm{iv}}^{rk}_{t_1}$. Cities (MSAs) are used for the regional dimension, while USPC for technology. City and technology cluster robust standard errors in parentheses. Time: $t_0 = [1870, 1890)$, $t_1 = [1890, 1930)$, $t_2 = [1930, 1950)$. First-stage relevance reported with Kleibergen–Paap F-statistic. Significance is denoted with $^{***}P < 0.01$, $^{**}P < 0.05$, $^{*}P < 0.1$.

$$\Delta \mathrm{nat}^{rk}_{t_1 \to t_2} = \theta \mathrm{nat}^{rk}_{t_1} + \beta_1 \mathrm{mig}^{rk}_{t_1} + \beta_2 e^{rk}_{t_1} + \delta^r + \iota^k + \eta^{rk}, \tag{7}$$

where $e^{rk}_{t_1} = \log(E^{rk}_{t_1})$. In Table 4, the reader can find the estimates of this specification.[17] We observe that expertise and patents of migrants are significant at the same time in all specifications, which indicate that the role of migration appears to be both *direct* (through the knowledge embedded in the migrants themselves) and *indirect* (through the links that the migrants provide with their home country).

5.3. The impact on technological evolution of US regions

The direct and indirect impact of migration on US innovation has the additional (but equally important) consequence to change the technological evolution of cities. While Akcigit et al. (2017) note that migration has driven the technological trajectory of the USA, and Moser et al. (2014) observe this in a specific technological field (i.e. chemistry), here we show that this process happens also at the regional level, with migration shaping the technological evolution of cities.

To highlight this point with more emphasis, we run here the analysis at the extensive margin. That is, instead of focusing on regions that have a specific technology, and study how the presence of migrant inventors influences its growth, in this section, we look uniquely at regions where a technology is missing.

17 Note that in Sections 5.2 and 5.3, we employ the cross-sectional specification in Akcigit et al. (2017) so that results are more comparable. For completeness, we report the results of the analysis using the specifications in Equations (1) and (4) (Supplementary Tables S.31–S.33). We find that results are robust in OLS, but not in IV (see discussion in Section 5.4).

Table 5. The extensive margin: Appearance of new city–technology combinations

Appearance of technological class k, in region r, time t_2	OLS (1)	OLS (2)	IV (3)	IV (4)
Patents of migrants (t_1)	0.315***	0.168***	30.129***	17.622***
	(0.059)	(0.049)	(7.247)	(5.102)
Expertise (t_1)	1.475***	0.570***	0.268	0.080
	(0.250)	(0.138)	(0.479)	(0.294)
Adjusted R^2	0.016	0.160		
Observation	93,191	93,191	93,191	93,191
F (first stage)			23.478	18.354
Dummies		k, r		k, r

Notes: All variables are in logs. Dependent variable: appearance of patenting activity by natives ($\text{appear}^{rk}_{t_1\to t_2}$). Explanatory variables: patenting activity by migrants ($\text{mig}^{rk}_{t_1}$) and expertise ($e^{rk}_{t_1}$). Instrumental variable (for $\text{mig}^{rk}_{t_1}$): $\tilde{\text{iv}}^{rk}_{t_1}$. Cities (MSAs) are used for the regional dimension, while USPC for technology. City and technology cluster robust standard errors in parentheses. Time: $t_0 = [1870, 1890)$, $t_1 = [1890, 1930)$, $t_2 = [1930, 1950)$. First-stage relevance reported with Kleibergen–Paap F-statistic. Significance is denoted with $^{***}P < 0.01$, $^{**}P < 0.05$, $^{*}P < 0.1$.

In this empirical design, we then drop all observations where in t_1 there is a patent by a native (i.e. if $\text{NAT}^{rk}_{t_1} > 0$). We then look at period t_2 to see if innovative activities in that technology have appeared. Using the indicator function, we write[18]:

$$\text{appear}^{rk}_{t_1\to t_2} := 1[\text{NAT}^{rk}_{t_2} > 0 \,|\, \text{NAT}^{rk}_{t_1} = 0]. \tag{8}$$

The corresponding econometric model is comparable to Equation (7):

$$\text{appear}^{rk}_{t_1\to t_2} = \beta_1 \text{mig}^{rk}_{t_1} + \beta_2 e^{rk}_{t_1} + \delta^r + \iota^k + \eta^{rk}. \tag{9}$$

We again find that migrants play a direct and indirect role, with both independent variables mig^{rk} and e^{rk} estimated to be positive and significant (see Table 5), although expertise is insignificant in IV regressions (see discussion in Section 5.4). The effect size of the role of migrants is large, but credible. One standard deviation increase in migration (0.028) leads to a 49% ($= 0.028 \times 17.6$) growth in appearance. That is an increase from 11% (the unconditional probability of a new patent from locals) to 18% ($= 0.11 \times e^{0.49}$))

5.4. Mechanism

While pinning down precisely the mechanism of knowledge spillovers is beyond the capacity of our dataset, it is worth discussing what we can infer from indirect evidence. First, as we highlight in previous section, the conceptual differences with which we constructed the IV and the expertise variable E are already hinting at the channel of knowledge diffusion—at least with respect to the origin of the knowledge that is being transferred. While

18 Alternatively, one could define the dependent variable in non-binary form ($\text{NAT}^{rk}_{t_2}$ conditional on $\text{NAT}^{rk}_{t_1} = 0$). We find that results are robust in OLS, but not in IV (see Supplementary Table S.34 and discussion in Section 5.4).

the IV suggests physical presence of knowledge, E indicates access to foreign expertise. As we found them both positive and significant, there is a reason to believe that migrants contribute directly (through their own knowledge) and indirectly (through the knowledge of their network) to accrue the technical capabilities of the USA. We note however that in some robustness tests (Supplementary Tables S.31–S.34), expertise is significant in OLS, but not in IV, suggesting that the direct channel is the predominant one.

Another indirect signal is provided by the timing of impact. It can be argued that—if the effect we observed is a spillover of foreign knowledge—the size of the impact will rapidly decline over time, which we indeed observe in Supplementary Figure S.2.[19]

Further, in Supplementary Figure S.3, we show the conditional distribution of patenting by natives, comparing those exposed to a low or high level of the instrument. We can clearly observe that the majority of the impact stems from the bottom half of the distribution. This is indicative of the fact that the impact of migrants may not come from the formalized environment of corporate innovation, but from the spreading of ideas by independent inventors.

One potentially relevant channel through which migrants may have benefited natives is by enabling spillovers to occur. We test this by exploring to what extent migrants have brought early-stage knowledge. Similarly to Bahar et al. (2020), we test whether migrants were more likely to participate in early-stage patents than natives. We consider early-stage patents in a USPC technological class as those that belong to the first decile of all patenting activity in that technology if patents are sorted in a chronological order by granting date. We consider two different aggregation levels at which a patent could be regarded as early-stage: the local level, which includes all patents in a given technology-MSA combination (Column 1 of Supplementary Table S.42); the national level, which includes all patents in a given technological class without taking geography into account (Column 2 of Supplementary Table S.42). Results show that there is indeed a positive correlation between the presence of a migrant in a patent and the likelihood that this patent is in an early stage.

5.5. Robustness

Our findings are robust to a variety of choices in the collection of data and in the design of the empirical analysis. In the Online Appendix, the reader can find a thorough discussion in Supplementary Section S.1, with all the relevant additional output reported in Supplementary Section S.2.

6. Conclusions

In this paper, we examined the impact of immigrants' patenting on the inventive activity of US native inventors from an historical perspective. We find that US regions greatly benefited from the presence of immigrant inventors: they gave rise to spatially localised knowledge spillovers that had positive effects on the patenting activity of native inventors. We show that the contribution of immigrant inventors was also indirect: they acted as

19 Contrariwise, a non-decaying pattern would have suggested either that the migrant access of foreign knowledge continued overtime or that the impact we observe on natives should be attributed to the migrant talent rather than the knowledge he brought. We thank an anonymous referee for pointing this out.

brokers of knowledge between their country of origin and the regions in the USA they happened to migrate to. Therefore, the positive effect of the immigrants' foreign expertise to the growth of US regional patenting is additional to the direct effect (i.e. patenting of immigrants). This diffusion mechanism is illustrated by the historian Thomas Hughes, when he discusses the involvement of Charles Steinmetz and other German physicists and mathematicians at the General Electric research laboratories. He argues that besides their inventive activity their greatest contribution was, in his words, to have 'introduced American engineers to advance mathematical modes of analyzing alternative current light and power systems. These modes greatly enhanced the problem solving abilities of engineering colleagues at GE' (Hughes, 2004, 161). These mathematical modes and the scientific method underpinning them were learned by the German researchers while working, experimenting and studying at their company or university laboratories in their home country. These immigrants embodied such tacit knowledge and carried it with them while migrating to the USA, where they shared it with their fellow colleagues and researchers. The knowledge spillovers generated by immigrants also shaped the technological evolution of US regions. Our results indeed show that US regions entered in new technological fields thanks to the knowledge imported by immigrants. This evidence aligns well with recent findings on contemporary migration (Bahar et al., 2020).

More in general our findings contribute to the debate initiated by historians on the role of community versus individual-based knowledge diffusion (Lissoni, 2018). Our results indeed show that the positive impact of immigrant inventors occurred during an era of mass migration, with open borders and no (or limited) restrictions to immigration. Our findings do not prove that open-border is an optimal immigration policy, but they do provide some food-for-thought for policy makers. For example, it can be argued that highly selective polices that strongly discriminate the low skilled might discourage also the migration of high-skilled immigrants: if the latter have a strong preference for diversity, they might indeed decide to move to more tolerant places (Kerr, 2018). In short, policy makers should consider that tighter immigration policies can generate unintended consequences; therefore, an efficient policy aimed at attracting skilled workers might require less, rather than more restrictions (Clemens and Pritchett, 2019).

Acknowledgements

We are indebted to the participants to LEREPS Seminar at University of Toulouse (November 2018), MIT-Media Lab Complexity Workshop (Boston, June 2018), Druid Conference (Copenhagen, June 2019) and the XL Aisre Annual Conference (September 2019). Any mistake remains ours.

A.M. acknowledges financial support from H2020-MSCA-IF (GOTaM Cities project—Grant Agreement ID: 789505) and RSA Membership Grant 2018.

Supplementary material

Supplementary data for this paper are available at *Journal of Economic Geography* online.

Conflict of interests

The authors declare that they have no conflict of interest.

References

Abramitzky, R., Boustan, L. (2017) Immigration in American economic history. *Journal of Economic Literature*, 55: 1311–1345.

Akcigit, U., Grigsby, J., Nicholas, T. (2017) Immigration and the rise of American ingenuity. *American Economic Review*, 107: 327–331.

Arellano, M., Bond, S. (1991) Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies*, 58: 277–297.

Bahar, D., Choudhury, P., Rapoport, H. (2020) Migrant inventors and the technological advantage of nations. *Research Policy*, 49: 103947.

Bandiera, O., Rasul, I., Viarengo, M. (2013) The making of modern America: migratory flows in the age of mass migration. *Journal of Development Economics*, 102: 23–47.

Borjas, G. J., Doran, K. B. (2012) The collapse of the Soviet Union and the productivity of American mathematicians. *The Quarterly Journal of Economics*, 127: 1143–1203.

Breschi, S., Lawson, C., Lissoni, F., Morrison, A., Salter, A. (2020) STEM migration, research, and innovation. *Research Policy*, 49: 104070.

Burchardi, K. B., Chaney, T., Hassan, T. A., Tarquinio, L., Terry, S. J. (2020) Immigration, Innovation, and Growth. Discussion Paper, National Bureau of Economic Research.

Card, D. (2001) Estimating the return to schooling: Progress on some persistent econometric problems. *Econometrica*, 69: 1127–1160.

Clemens, M. A., Pritchett, L. (2019) The new economic case for migration restrictions: an assessment. *Journal of Development Economics*, 138: 153–164.

Ganguli, I. (2015) Immigration and ideas: What did Russian scientists "bring" to the United States? *Journal of Labor Economics*, 33: S257–S288.

Gibson, C., Lennon, E. (1999) Historical Census Statistics on the Foreign-Born Population of the United States. 1850TO1990.

Goldin, C. (1994) *The political economy of immigration restriction in the United States, 1890–1921*. In C. Goldin and G.D. Libecap (eds), *The Regulated Economy: A Historical Approach to Political Economy*, pp. 223–258. Chicago and London: University of Chicago Press.

Goldsmith-Pinkham, P., Sorkin, I., Swift, H. (2018) Bartik Instruments: What, When, Why, and How. Discussion Paper, National Bureau of Economic Research.

Hall, B. H., Jaffe, A. B., Trajtenberg, M. (2001) The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools. Discussion paper, National Bureau of Economic Research.

Hatton, T. J., Ward, Z. (2018) International migration in the Atlantic economy 1850–1940. In C. Diebolt and M. Haupert (eds), *Handbook of Cliometrics*, pp. 1–29. Springer, Berlin, Heidelberg.

Hatton, T. J., Williamson, J. G. (1998) *The Age of Mass Migration: Causes and Economic Impact*. Oxford University Press on Demand.

Hughes, T. P. (2004) *American Genesis: A Century of Invention and Technological Enthusiasm, 1870–1970*. University of Chicago Press.

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

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

Jaeger, D. A., Ruist, J., Stuhler, J. (2018) Shift–Share Instruments and the Impact of Immigration. Discussion paper, National Bureau of Economic Research.

Kerr, S. P., Kerr, W., Özden, Ç., Parsons, C. (2016) Global talent flows. *Journal of Economic Perspectives*, 30: 83–106.

Kerr, W. R. (2007) The Ethnic Composition of Us Inventors: Evidence Building from Ethnic Names in US Patents.

Kerr, W. R. (2018) *The Gift of Global Talent*. Stanford University Press.

Kerr, W. R., Lincoln, W. F. (2010) The supply side of innovation: h-1B visa reforms and US ethnic invention. *Journal of Labor Economics*, 28: 473–508.

Khan, B. Z. (2005) *The Democratization of Invention: Patents and Copyrights in American Economic Development, 1790–1920*. Cambridge University Press.

Lee, D. L., McCrary, J., Moreira, M. J., Porter, J. (2020) Valid t-ratio inference for IV. arXiv preprint arXiv:2010.05058.

Lissoni, F. (2018) International migration and innovation diffusion: an eclectic survey. *Regional Studies*, 52: 702–714.

Miguelez, E., Temgoua, C. N. (2019) Inventor migration and knowledge flows: a two-way communication channel? *Research Policy*, 49: 103914.

Moser, P., San, S. (2019) Immigration, Science, and Invention: Evidence from the 1920s Quota Acts. Unpublished manuscript.

Moser, P., Voena, A., Waldinger, F. (2014) German Jewish émigrés and US invention. *American Economic Review*, 104: 3222–3255.

Petralia, S. (2019) HistPat International Dataset. Harvard Dataverse. https://doi.org/10.7910/DVN/QT4OJS

Petralia, S., Balland, P.-A., Rigby, D. L. (2016) Unveiling the geography of historical patents in the United States from 1836 to 1975. *Scientific Data*, 3.

Rodriguez-Pose, A., Von Berlepsch, V. (2014) When migrants rule: The legacy of mass migration on economic development in the United States. *Annals of the Association of American Geographers*, 104: 628–651.

Sequeira, S., Nunn, N., Qian, N. (2020) Immigrants and the making of America. *The Review of Economic Studies*, 87: 382–419.

Sokoloff, K. L. (1988) Inventive activity in early industrial America: evidence from patent records, 1790–1846. *The Journal of Economic History*, 48: 813–850.

Tabellini, M. (2020) Gifts of the immigrants, woes of the natives: lessons from the age of mass migration. *The Review of Economic Studies*, 87: 454–486.

Tesla, N. (2011) *My Inventions and Other Writings*. Penguin.

Appendix A

A. Descriptive statistics

Table A1. Type of technology by nationality

	GB	DE	SW-NO	AT-HU	RU	IT	CA	USA
Others	0.357	0.340	0.351	0.416	0.499	0.466	0.419	0.441
Mechanical	0.369	0.402	0.430	0.366	0.283	0.346	0.360	0.366
Electrical and Electronic	0.127	0.144	0.115	0.100	0.123	0.076	0.080	0.074
Drugs and medical	0.013	0.008	0.004	0.007	0.010	0.018	0.014	0.013
Computers and communications	0.024	0.010	0.017	0.027	0.012	0.019	0.048	0.017
Chemical	0.109	0.096	0.083	0.085	0.073	0.074	0.079	0.089

Notes: Our dataset is classified according to the USPC, which is provided by the USPTO. It classifies patents into technological classes according to the type of invention to which they claim rights. There are currently more than 400 different technological classes in use, and whenever a new class is created, or an existing one re-defined, all patents are re-classified to maintain temporal consistency (see http://www.uspto.gov/learning-and-resources/electronic-bulk-data-products). In addition, patents can be grouped into economically relevant categories (Chemical, Computer and Communications (C&C), Drugs and Medical (D&M), Electrical and Electronics (E&E), Mechanical and Others). See Hall *et al.* (2001) for details. The concordance is available at http://www.nber.org/patents/. The US shares are calculated using HistPat data (Petralia et al., 2016).

Table A2. Descriptive statistics of the main datasetA.2.1 All observations

Variable	*N*	Mean	SD	Min	Max
Number of patents of natives	763,110	2.737	25.256	0.000	2709.000
Number of patents of migrants	763,110	0.017	0.327	0.000	39.000
Total number of patents	763,110	2.754	25.399	0.000	2715.000
Instrumental variable	763,110	0.016	0.155	0.000	23.096
Expertise	763,110	0.016	0.307	0.000	49.317

Table A2.2. Only positive observations

Variable	*N*	Mean	SD	Min	Max
Number of patents of natives	163,802	12.750	53.329	1.000	2709.000
Number of patents of migrants	6625	1.993	2.900	1.000	39.000
Total number of patents	164,238	12.797	53.563	1.000	2715.000
Instrumental variable	321,094	0.037	0.237	0.000	23.096
Expertise	148,278	0.084	0.691	0.000	49.317

Table A2.3. Log(x + 1)

Variable	N	Mean	SD	Min	Max
Number of patents of natives	763,110	0.336	0.816	0.000	7.905
Number of patents of migrants	763,110	0.008	0.097	0.000	3.689
Total number of patents	763,110	0.337	0.818	0.000	7.907
Instrumental variable	763,110	0.012	0.070	0.000	3.182
Expertise	763,110	0.010	0.080	0.000	3.918

Notes: In the main dataset, we observe patenting activity of natives and migrants divided by region r, technological class k, and decade t. With 366 MSAs, 417 US Patent Classes, and 5 decades (1900–1940), we have $366 \times 417 \times 5 = 763{,}110$ observations, as reported in the top third of the table. Appendix A.1.2 shows the descriptive statistics, restricting the data to only positive observations. It is easy to see that about 19% of observations have at least one patent in the region-class-decade. Only 0.9% of observations instead have a migrant-authored patent. Appendix A.1.3 shows the dataset in logs. Instrument and expertise variables are defined in Equations (3) and (6), respectively.