Why shutting the doors to immigration is bad for innovation: lessons from the age of mass migration in the US

1. Introduction

Global talents fuel the growth of the hosting economies with their ideas, skills and creativity (Kerr, 2018). The importance of the link between international migration and innovation has been highlighted by a growing number of empirical studies that have investigated how high-skilled migrants contribute to scientific and technological change in host economies (Breschi et al., 2020; Kerr, et al. 2016; Lissoni, 2018). Extensive literature has provided robust evidence on the role of high-skilled migration in sending (Iasio & Miguelez, 2022) and destination countries (Kerr & Lincoln, 2010) and at different levels of analysis, including countries (Fassio et al., 2019), regions (Miguelez & Morrison, 2023) and firms (Ozgen et al., 2014). Taken as whole, this body of work shows that receiving economies largely benefit from the influx of high-skilled immigrants. The underlying mechanism is that high-skilled migrants bring with them the tacit component of knowledge, which will be otherwise hard to transfer over long distances (Audretsch and Feldman, 1996), and they share it with peers in the organisations and places they happen to land in (Choudhury, 2016). This process activates multiple mechanisms of knowledge recombination, which ultimately spur the creation of novel and impactful innovation (Morrison, 2023). The importance of the phenomenon has been also recognised by policy makers, up to the point that several countries have designed incentive schemes to attract the best and brightest talents (World Bank, 2018).

However, despite their importance, international workers face multiple obstacles that impede them to travel and work in the host countries (Choudhury, 2022). In recent years, several advanced economies have tightened their immigration policies to prevent the arrival of foreign workers (OECD, 2023). Examples of such policies include the executive orders issued by the Trump administration in the US in 2017 and 2020, which prevented the entry of citizens from seven predominantly Muslim nations (Stone & Wadman, 2017) and limited the emission of H1-B visas for foreign workers, respectively (Chishti, Pierce, & Olsen-Medina, 2020). Another prominent example is the Quota Act, which was enacted in the United States in the 1920s to limit the influx of immigrants from Eastern and Southern European (hereafter ESE) countries (Goldin, 1994). The Quota Act, much like contemporary immigration policy, emerged in a political climate of backlash against immigrants from certain origins (e.g. Italy, Poland) who were seen as culturally distant and racially inferior to those born in the US (Greenwood & Ward, 2015).

In this paper, we focus on this historical event (i.e. the age of mass migration) and on a policy measure (i.e. the Quota Act) that, according to its proponents, was intended to limit the arrival of poor and unskilled immigrants, but instead also rejected scientists and skilled workers (Moser & San, 2020). Our analysis aims at quantifying the potential loss that this policy restriction had on the inventive capacity of US counties.

We argue that a limitation to the arrivals of ESE inventors would generate a direct effect on the inventive capacity of US counties because, ceteris paribus, the total pool of inventors available to these counties would decline. In addition, we argue that there is also an indirect negative effect due to the loss of knowledge spillovers from immigrant inventors to US-born inventors. Since knowledge spillovers tend to be localised (Jaffe et al, 1993), we would expect them to be strong in the places where immigrant inventors would work and patent. A significant decline in ESE inventors would then mean fewer opportunities for US-born inventors to interact with them and, in turn, benefit from their ideas. Since immigrants and inventor immigrants in the US clustered spatially along ethnic lines (Abramitzky & Boustan, 2017; Diodato, et al., 2022), the regions typically populated by ESE inventors would also be the ones that suffered the most from this decline in immigration. The asymmetric nature of the quota act has also important methodological implications, as it provides a quasi-experimental setting to assess the causal impact of a decline in immigration on various economic outcomes, including invention (Ager & Hansen, 2017; Campo, et al., 2022; Moser et al., 2014; Tabellini, 2020). In our work, we compare changes in patenting after the introduction of the quotas in US

county-technology pairs that were exposed to ESE inventors before the quotas with changes in patenting after the quotas in US county-technology pairs that were not (or less) exposed to this group before the quotas.
The empirical analysis relies on an original dataset of US historical patent documents of about 2.5 million patents filled by US-born and European-born immigrant inventors between 1860 and 1940 (Diodato et al. 2022). Since the contribution of immigrant inventors to the US technological system was relevant both in quantitative as well as in qualitative terms (Hughes, 2004), text mining and machine learning procedures have been implemented in order to identify breakthrough innovations, measured as the top 10% of quality patents.
Our results show that the quota system had remarkable negative effects on the inventive capacity of US counties. The impact was both direct, with a decline of the total number of inventions as well as indirect, via the drying up of local spillovers for US-born inventors, who patented less. In addition, the negative impact was also qualitatively significant, as we observe a substantial decline in breakthrough inventions.
Our work relates to different streams of literature in economic geography, innovation studies and economics. It speaks to the stream of studies that have recently investigated the link between migration and innovation (Breschi et al. 2020; Kerr et al. 2016; Lissoni, 2018). In particular, it contributes to empirical work that has analysed this link from a historical perspective, such as those that have focused on the age of mass migration in the US (Diodato et al., 2022; Rodríguez-Pose & Von Berlepsch, 2014; Sequeira, et al., 2020). Our work also relates to the recent literature in economic geography advocating for the importance of external linkages for regional innovation (Boschma, 2022; Fitjar, and Rodríguez-Pose, 2011; Miguelez & Moreno, 2018) and international knowledge diffusion (Breschi et al. 2009; Breschi et al. 2017; Choudhury, 2016; Morrison, 2023). Finally, our empirical findings add to the literature investigating the impact of tighter immigration policies on economic outcomes (Clemens, 2011). In this latter stream of studies, some very recent works have tried to quantify the impact of restrictions on innovation (e.g. Moser and San, 2020). We complement this literature in three important ways. First, we adopt a geographical perspective, which is important since immigrants were remarkably concentrated in space along ethnic lines (Abramitzky and Boustan, 2017). Second, we focus on the qualitative impact of the quotas. Immigrants inventors proved to be pioneers in many technological fields (Akcigit, et al. 2017), so consequences are expected not only on fringe patents but also on high-quality innovation (i.e. breakthrough innovation). Thirdly, our analysis looks at a broad group of inventors beyond scientists, who often had no formal education, but were highly represented among inventors in this historical period (Hughes, 2004; Khan, 2005).
Though historical in essence, this work provides important insights for today's policy makers. Tighter immigration policies, such as the 1920s quota act, can result in unintended consequences that oppose the original intentions of proponents. Because of the widespread and potentially long-lasting impact of these consequences, policymakers should exercise caution when designing and implementing such policies.
The remainder of the paper is structured as follows. Section 2 presents the theoretical background. Section 3 introduces the historical background. Section 3 illustrates the data sources. Section 4 discusses the empirical design and section 5 outlines the main results. In section 6 we present a battery of robustness checks. Section 7 concludes.

2. Theoretical Background

The diffusion of knowledge remains a foundational topic in the field of economic geography. The literature has extensively documented the localized nature of knowledge dissemination and innovation and empirical investigated how knowledge spillovers cross spatial boundaries (Asheim & Gertler, 2005; Breschi & Lissoni, 2001; Jaffe, Trajtenberg, & Henderson, 1993). Central to this discussion is the concept of tacit knowledge (Polanyi, 1962). The tacit, personal, and inherently idiosyncratic nature of knowledge presents significant barriers to its smooth circulation over large distances (Audretsch and Feldman, 1996). Therefore, the diffusion of knowledge predominantly relies on its embodiment within agents who are instrumental in its creation, emphasizing the role of mobility as a crucial conduit for knowledge transfer (Breschi & Lissoni, 2009). This explains why migration stands out as an effective way to overcome the inherent "stickiness" of knowledge to particular places. By allowing knowledge to move alongside individuals, migration acts as a means to go beyond the geographical limitations that impede knowledge flows. Therefore, high skilled migrants act as bridges across distant places (Saxenian, 2006) allowing host economies to access diverse and non-redundant knowledge sources that help them to escape from lock-in and decline. More than that, migrants allow regional economies to recombine local with external knowledge, which can spur novel and impactful innovation (Miguelez and Morrison, 2023).

Building on these arguments, in the last decade a stream of literature crossing economic geography, innovation studies and economics among others has produced a significant amount of quantitative evidence on the link between migration, innovation and knowledge diffusion (Breschi et al. 2020; Lissoni, 2018; Kerr et al, 2017). Many studies in this emerging literature show that the contribution of high-skilled immigrants to innovative activity is substantial and growing over time. For example, looking at patent applications Kerr and Lincoln (2010) have found that inventors of Indian and Chinese ethnic origins have increased their share of patenting, moving from less than 2% to 6% and 9%, respectively. Likewise, Hunt and Gauthier-Loiselle (2010) find that 6.2% of STEM immigrants have been granted a patent relative to 4.9% of US natives.

A great deal of attention has also been devoted to the labour market impact of skilled immigrants, as the positive effect in terms of higher patenting could be outweighed by a decline in patenting of the natives. With few exceptions (Borjas and Doran, 2012), the empirical evidence suggests that immigrant don't crowd-out natives, so the overall effect tend to be positive or at least non-negative (Ganguli, 2015; Hunt & Gauthier-Loiselle, 2010).

Another stream has asked if migrant inventors can contribute to triggering new technological trajectories in the host economies. Evidence suggests that immigrant inventors, by bringing with them the knowledge that is new to the region or the organisation they move to, can recombine it locally, and this gives rise to innovation which is unrelated to the one already present in the region (DiIasio & Miguelez, 2022; Miguelez and Morrison, 2023). Migrants also act as knowledge brokers by connecting distant places. They build conduits that allow the transfer of knowledge that is specific to the place of origin and diffuse to the place of destination via mobility and diaspora networks (Breschi et al. 2017; Choudhury, 2016).

Next to the works on contemporary migration, a subset of quantitative studies has focused on specific historical events (Lissoni, 2018). Among them, the US and the age of mass migration have attracted a good deal of attention (Diodato et al. 2022; Rodriguez-Pose and Von Berlepsch, 2014; Sequeira, et al. 2020; Tabellini, 2020). For example, Moser et al., (2014) document that German Jewish scientists, who fled Nazi Germany after 1933, made a crucial contribution to the development of new technological fields in field of chemistry in the US. Akcigit et al. (2017) find that immigrant inventors had a long-term impact on innovation in the US, especially in emerging technological fields. Diodato et al. (2022) further show that immigrant inventors contribute to the emergence of new specialisation across US regions by bringing knowledge from their country of origin.

Another recent stream of studies has more directly asked the question if restrictive immigration policies impact on the innovation capacity of host economies. Some works have examined the effects of changes in attraction policies that target high-skilled workers, such as the H1-B Visa in the US. The findings indicate that for example reducing the number of visas available to high-skill workers produces a negative impact on innovative capacity (Kerr & Lincoln, 2010; Choudhury et al. 2022). Other recent analyses confirm that a negative sign holds also for policies that don't specifically target high-skilled workers, but actually are designed to limit the arrivals of selected foreign nationalities. For example, the executive orders issued by Trump in 2017 had a negative impact on the US economy and its capacity to attract or retain students (Todoran & Peterson, 2020; Van De Walker & Slate, 2019). Similar negative effects have been found for the US after the introduction of the Quota Act in the early 1920s. Moser and San (2020) report that the quotas had a remarkable negative impact on the attraction of foreign scientists to the US, which in turn had a negative impact on the inventive activity of US-born inventors, who patented 62% fewer inventions. Similarly, Arkolakis et al. (2020) show that the quota act had a negative qualitative impact on the US technological production. They also project that a restriction on immigration in 1880 would have meant a significant reduction in US GDP per capita in the 1920s of around 30%.

In summary, the above evidence suggests that immigrant inventors tend to have a positive effect on the inventive capacity of the host economy; therefore, tighter immigration policies may be detrimental to innovation by limiting the arrival of immigrant inventors. Moreover, since native inventors benefit from the knowledge spillovers of immigrant inventors, a reduction in their number in certain regions would have a potentially negative effect on the productivity of native inventors in those regions.

3. Historical background

More than 30 million people migrated to the U.S. during the so called Age of Mass Migration, a period that goes from the mid 1850 till 1924 (Hatton, 1998). The first and second waves were characterised by British and Irish, plus German and Scandinavian nationals, respectively. By 1890, 90% of migrants were from those North-Western European countries. In the early 20th century, with the declining cost of travelling and the decrease in time spent on board transatlantic vessels, new groups of migrants reached the American shores. These immigrants were -on average- younger, less skilled, more likely to be males, and unmarried (Abramitzky & Boustan, 2017). The share of ESE inventors jumped during a few decades from 8% in 1870 to 80% in 1910. For example, the share of foreigners in the labour force of some US cities, like Boston or New York, was nearly 50% of the total.

This massive influx of immigrants also coincided with the transformation of the US economy from a primarily rural to a developed and industrialised nation by the end of the XIX century. By the beginning of the XX century, the US had become the technological leader and the most innovative nation in the world in terms of the number of patents and breakthrough innovations (Arkolakis, et al. 2020; Hughes, 2004).

Meanwhile, cultural and religious differences encouraged the emergence of anti-immigrant sentiment, which built consensus around the idea that ESE inventors would have a negative influence on the cultural, economic and social development of the US. In 1894, three Harvard alumni founded the Immigration Restriction League, an influential movement in American politics at the time. The founders believed that the new waves of migrants from Southern and Eastern European countries were a threat to the “American way of life” as they defined the Anglo-Saxon background of the American population. They campaigned for the literary test that the US congress finally adopted in 1917 to restrict low-skilled immigrants.

Between 1921 and 1924, the US Congress passed the so-called "Immigration Act" or "Johnson-Reed Act,” which limited the number of visas for foreigners. First, the emergency Quota Act of 1921 imposed a quota of 3% of the nationals of each European country according to the 1910 census. As the reference census was in 1920, southern and eastern Europeans were limited, but still had a significant share of the quotas. As a result, the immigration act was tightened, and the Congress again set the quota for immigrant visas at 2% of the total number of people of each nationality in the US according to the 1890 census. This meant a significant reduction of visas granted to southern and eastern European migrants, who in 1890 made up less than 10% of the total foreign population, as the majority of the quota allocated would then go to northern and western Europeans (Tabellini, 2020). The country then went from having almost open borders for Europeans to restricting immigration mainly for southern and eastern Europe. Since then, the US has restricted immigration until the early 1960s.

4. Historical patent data and immigrant inventors

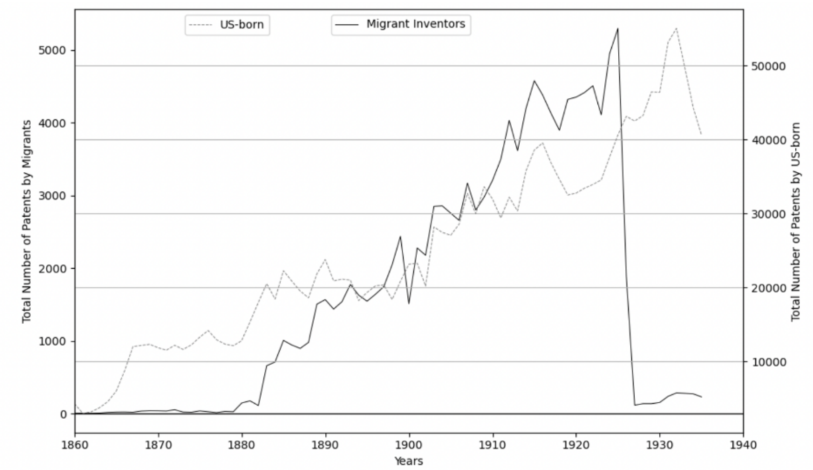
This paper relies on an original dataset of historical USPTO patent documents containing information on inventors' first and last names, nationality, place of residence (state and county or city), and the full description of each patent. Google Patents also provides the Cooperative Patent Classification codes for all the technologies used in the patent dataset. We have built our dataset closely following the methodology discussed in Diodato et al., (2022). In addition, we have improved the Diodato et al. (2022) dataset in two ways: first, by applying updated OCR techniques, we have retrieved a larger number of patent documents from Google

Patents; second, by applying recent NPL models (spaCy library in phyton), we have been able to more accurately identify the names and geographic locations of inventors from patent documents. These improvements have allowed us to identify a larger number of immigrant inventors in patent documents. The final dataset consists of a total of 2,122,928 patents from 1840 to 1940 and it includes around 60,000 unique immigrant inventors, the majority of whom are European (e.g. British, German, French, Austro-Hungarian, Swiss, Swedish, Russian and Italian).

Our analysis uses also the IPUMS full count decennial census from 1900 to 1940. From IPUMS, we collected economic and demographic information of US counties. In particular, we used the share of European migrants in each county-decade and other economic and demographic output variables such as total area in square miles, total population, and the amount of goods produced then.

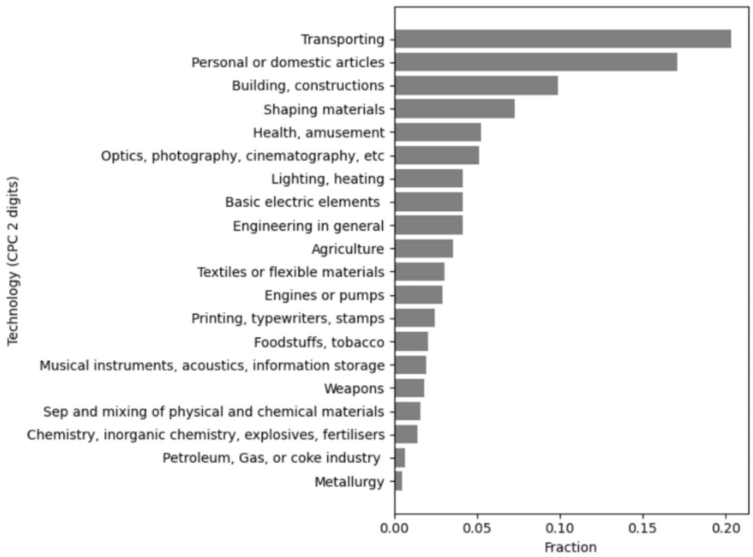
Figure 1 shows the total number of patents granted to immigrant inventors and those granted to US-born inventors. Looking at the two trends, it is clear that the immigration restrictions introduced between 1921 and 1926 had an impact on the patenting activity of immigrants. The total number of patents by immigrants fell sharply after 1926, while the trend in patents by US-born inventors was mainly unaffected and continued to grow steadily over time.

Figure 1: Total number of patents by immigrant inventors and US-born inventors.



In Figure 2, we explore the technological specialisation of immigrant inventors. The figure presents the ranking of the top 29 leading technological domains among ESE inventors. The frequencies are given by a ratio of 2-digit technological classes in which ESE inventors were prolific before the quotas. We observe that ESE inventors were particularly active in emerging technologies, such as transport, electricity and chemical products. Annex C provides the complete list of the 29 domains.

Figure 2 – Pre-quota patenting of ESE immigrant inventors by technological class



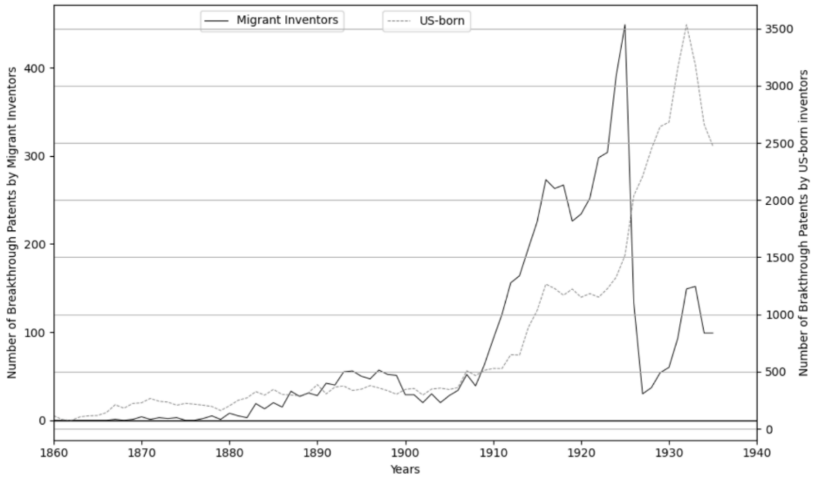
We have also constructed statistics on high-quality patents. Citations and patent classifications are the standard ways to identify these inventions for contemporary patents (Squicciarini, Dernis, & Criscuolo, 2013). However, as we are dealing with historical patents from before 1947, when the referee system was not yet in place, citations are not a reliable proxy for quality. Other approaches have been used to overcome this problem (Arts & Veugelers, 2015; Capponi, Martinelli, & Nuvolari, 2022; Kelly, Papanikolaou, Seru, & Taddy, 2018). In our work, we follow the methodology of Arts et al. (2021) and Kelly et al. (2018). According to this methodology, for a patent to be classified as a breakthrough, it must meet two requirements: it has to be novel compared to the state of the art, and it has to have high impact on future patents. Inspired by recent studies, we have classified novelty and impactfulness of patents by using text-mining techniques. We have vectorised words in the text of each patent document and measured the cosine similarity between all the patents in the sample. To build the breakthrough innovation index, we have identified patents in the top 10% of their year cohort in novelty[1] (meaning they are the most dissimilar patents to others) and the top 10% of the patents with more influence in the future[2]. Breakthrough inventions are those that are both novel and impactful.

[1] We determined whether a patent was novel by vectorising the text of each patent and calculating the cosine similarity score of each patent with all patents from the previous 10 years. This is what we call a "backward similarity score". The more similar a patent is to others in the past, the less novel it is. Therefore, we subtracted one from the backward similarity score and ranked the scores to find the top 10% in a given year. Note that each patent is ranked from the top 10% quantile of the same year cohort to control for language use and year of application.

[2] Usually, a high-impact patent is one through which many other patents are connected to. It is a parent patent cited within the top 10% of its year cohort because of its relevance and importance. After vectorising all patents, we computed: 1) the backward cosine similarity score of a given patent with all patents filed within ten years of the focal patent; 2) the forward cosine similarity score of a particular focal patent with all the patents applied within ten years after the focal patent. To build a high impact measure, we obtained a final ratio by dividing the forward cosine similarity score /backward cosine similarity score for each patent and penalising and weighting for the number of words in the sample. We controlled for the plausible "old" English language use by comparing patent vectors within a ten-year window and ranking the scores based on their respective year-cohort. As a result, patents with a higher impact ratio are more influential in forward cosine similarity than backward cosine similarity. The top 10% of these scores within the year cohort are considered impactful patents.

Figure 3 shows the evolution of breakthrough patents in the US. The figure documents a sharp decline in the total number of breakthrough innovations by immigrant inventors after the introduction of the quotas. In contrast, the trend of breakthrough patents by US-born inventors has been steadily increasing.

Figure 3: Total number of breakthrough innovations by immigrant and US-born inventors.



5. **Empirical strategy**

We apply a difference-in-difference strategy to estimate the effect of the quotas on the inventive activity of US counties. The tightening of immigration policy following the implementation of the Quota Act was an exogenous shock that affected US counties asymmetrically. The asymmetric nature of the shock is due to the strong clustering of European immigrants along ethnic lines (Abramitzky and Boustan, 2017). In our case, it is important to highlight that immigrant inventors also followed a similar pattern of geographical concentration (see Figures D.1 and D.2 in the Appendix) (Diodato et al., 2022). Therefore, we identify US county-technology pairs that were particularly exposed to ESE inventors. These are the 'regions' where ESE inventors would be particularly active and patenting in specific technologies. Therefore, ESE regions are counties where ESE inventors were active in patenting in specific technological fields and represent the treatment group in our empirical strategy. To ensure that our analysis is robust, we have computed four different exposure measures for ESE regions. They differ in that each uses a different threshold to assign counties/technologies to the treatment or the control group. The first, which is the baseline in our analysis, assigns to the "treatment" group all region-technology pairs with at least one or more ESE inventors. For example, suppose that at least one East or South European inventor resident in Brooklyn County patents in the field of transportation. In this case, the county-technology pair "Brooklyn and Transporting" is considered part of the "treatment" group.

The second variant assigns a county-technology pair to the treatment group if two or more ESE inventors reside in that county and are active inventors in a given technological class. The third threshold is computed as the ratio of ESE inventors to the number of NWE (North and Western European) inventors in any county/technology. In this case, the ratio is computed as follows:

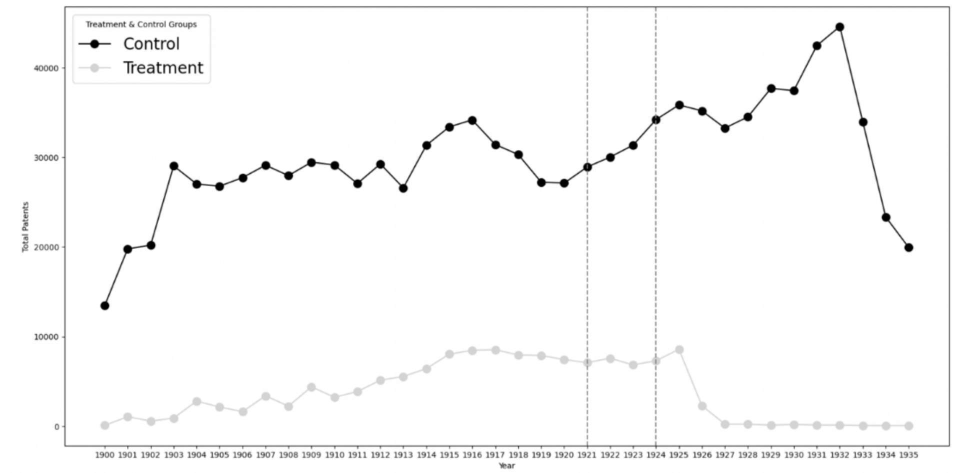
$$Treatment = 1\ if\ \frac{\Sigma\, ESEmigrantinventors_{rf}}{\Sigma\, NWEmigrantinventors_{rf}} > 1\ ;$$

We assign to the treatment group counties r / technologies f whose ratio of ESE inventors to NWE inventors is greater than 1. Once the treatment and control groups are constructed, we test the causal effect of the quotas by comparing changes in patenting after the quotas of US county-technology pairs that were exposed to ESE inventors before the quotas with changes in patenting after the quotas of US county-technology pairs that were not exposed to ESE inventors before the quotas.

In order to attribute patents to the ESE regions we had to take into account the decennial structure of the census data. The census years considered for the analysis are 1910, 1920, 1930 and 1940. However, the policy shock took place between 1921 and 1924, and we can argue that the real effect would have taken place from 1925 and onwards. To be accurate in aggregating the number of patents and the number of breakthrough innovations in each county, each technology and decade, we impute all patents granted until 1925 to 1920's decade.

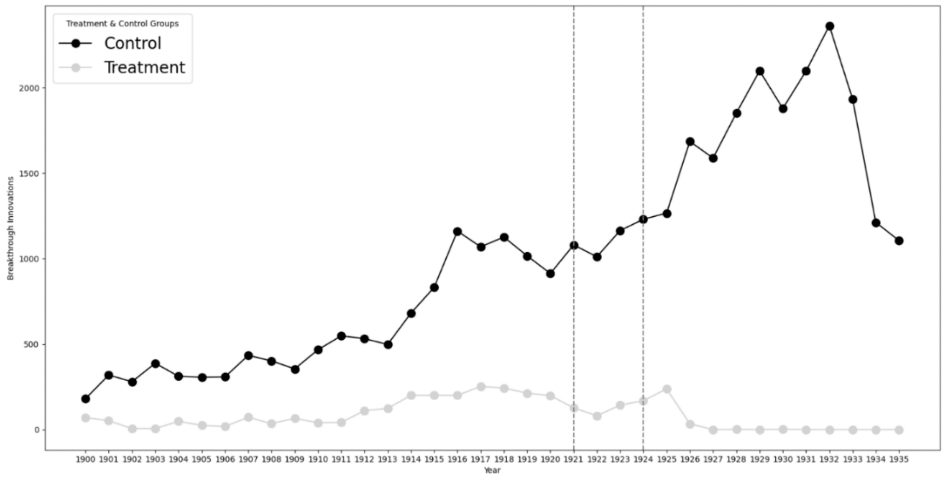
The parallel-trends assumption is a prerequisite for the implementation of a difference-in-differences strategy. We assume that before the shock, the trends in the outcome variables (i.e. patenting) should have been similar and that if the quotas had been introduced in 1924, the trend in the treatment would have changed radically but remained stable in the control group. As shown in Figures 4 and 5, the trends look similar before quotas, but diverge afterwards. To make them more readable, we have aggregated the patents at the level of country and technology year instead of decade. The outcome of the variable of interest (in this case, the total number of breakthrough innovations per county per technology class) follows a similar pattern in both counties/technologies (i.e. those exposed to at least one Eastern and Southern European immigrant inventor– treatment - and those counties/technologies not exposed to this particular group of immigrant inventors). We observe a smooth decline (or stability) of exposed counties after the First World War, partly recovered after the introduction of the first quota act in 1921. However, when the second quota was introduced in 1924, we can see a sharp decline in patenting activity for exposed counties already in 1925 as compared to the counterfactual.

Figure 4 Total number of patents in the treatment and control groups



Note: the treatment group (grey line) includes technology-county pairs in which there was at least one ESE inventor before the Quota Act.

Figure 5 Total number of breakthrough patents in the treatment and control groups



Note: the treatment group (grey line) includes technology-county pairs in which there was at least one ESE inventor before the Quota Act.

6. Empirical Results

6.1 Effect on total patenting in US counties

To study the causal impact of the quotas on patenting in US counties, we first estimate the following OLS model:

$$lnY_{rft} = \beta_0 + \beta_1\left(ESEregion_{rft} * post_t\right) + \beta_2 ESEregion_{rft} + \beta_3 post_t + X' + \varphi_r + \delta_t + \gamma_f + \lambda_{rt} + \theta_{rt,ft} + \varepsilon_{rft} \quad (1)$$

Where the dependent variable lnY_{rft} is the log of the total number of patents i filled by US inventors, in time t and technology field f in county r. We also test a specification where the dependent variable is given by the total number of patents made by US-born inventors only. The variable $ESEregion_{rtf}$ takes the value 1 if the invention was made in an county r exposed to ESE inventors at time t and technology f. The variable $post_t$ takes the value 1 if the observation corresponds to the 1930 and 1940 decades and 0 if the observation corresponds to 1910 and 1920 (pre). X' is a vector of controls at county level, such as population, share of immigrants, and other variables that proxy for the level of economic development of a county (i.e. value of their declared production of goods and type of crops[3]). The model includes state fixed effects (φ_r), to control for time-invariant characteristics that differ across US states (e.g. institutions); time fixed effects, δ_t, to control for temporal shocks common to all county-technology pairs. Technology fixed effects γ_f to control for time-invariant features peculiar to each technological field. In some specifications we have also included the interaction terms λ_{rt} and θ_{ft}. λ_{rt} is an interaction of state and time-fixed effects to account for time-varying factors, such as changes in policies that affected specific US states; θ_{ft} is the interaction between technology and time to control for the time-varying factors in specific technologies and their evolution over time. To control for the inconsistency in standard errors resulting from serial correlation among the many observations within the same county, we cluster errors at the county level (Abadie, Athey, Imbens, & Wooldridge, 2017).

Table 1 reports the results of our baseline equation (1). We observe a significant and negative coefficient of the variable $ESEregion_{rft} * post_t$ in model 1 ($\beta_1$is -0.845) that indicates a sharp decline in invention after 1924. US inventors in ESE regions produced between 57% and 41% less patents than their peers in the control

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[3] Unfortunately, we lack of uniform measurements in the IPUMS census to control for the income or GDP per county, other than the value of crops, vegetables and fruits production of those counties. The industrial production, is only available for the decades 1920 and 1930, namely, the "post" time in our sample, so we had to discard it.

group[4] (see Columns 1 to 4 in Table 1). Findings are robust to the different set of fixed effects, including the interaction terms (see Columns 2, 3 and 4 in Table 1).

Table 1: The effect of the Quota Act on the inventive activity of US counties

	(1)	(2)	(3)	(4)
VARIABLES	ln Total Patents	ln Total Patents	ln Total Patents	ln Total Patents
Exposure	2.397***	2.038***	1.988***	1.833***
	(0.000)	(0.000)	(0.000)	(0.000)
Did	-0.845***	-0.797***	-0.725***	-0.515***
	(0.000)	(0.000)	(0.000)	(0.000)
shareese	0.042***	0.022***	0.022***	0.022***
	(0.000)	(0.000)	(0.000)	(0.000)
totpop_std	0.250***	0.239***	0.243***	0.244***
	(0.000)	(0.000)	(0.000)	(0.000)
area_std	-0.017***	-0.009	-0.008	-0.008
	(0.001)	(0.200)	(0.284)	(0.283)
cropval_std	0.089***	0.086***	0.088***	0.088***
	(0.000)	(0.000)	(0.000)	(0.000)
vegaval_std	0.023	0.007	0.005	0.005
	(0.400)	(0.727)	(0.800)	(0.793)
fruitval_std	0.002	-0.002	-0.004	-0.004
	(0.899)	(0.873)	(0.769)	(0.776)
Constant	0.305***	1.508***	1.747***	1.966***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	350,001	350,001	350,001	350,001
R-squared	0.316	0.441	0.445	0.469
Decade FE	YES	YES	YES	YES
Tech FE	NO	YES	YES	YES
State FE	NO	YES	YES	YES
Decade#State FE	NO	NO	YES	YES
Decade#Tech FE	NO	NO	NO	YES

Robust pval in parentheses *** p<0.01, ** p<0.05, * p<0.1

Note: Difference in Differences on the effect of the quota restrictions on Ttotal Patents in its logarithmic form. The first column considers only Time FE; the second one, Technology, State and Time FE; the third one adds the State#Time interaction dummy, and the last column reports all the FE terms, including the interaction dummy Technology#Time FE; this model is computer using the sample with only US-born total patents, i.e. patents produced by US-born and migrant inventors only.

Table 2 presents the OLS estimates for US-born inventors only. Notably, the size of the coefficient estimates is remarkably large and similar to those found for all US inventors ($\beta_1$is -0,831). On average, a US born inventor living in a county with technologies exposed to ESE inventors would have between 56% and 40%[5] fewer patents after the quota (see Columns 1 to 4 in Table 2).

Table 2: The effect of the Quota Act on the inventive activity of US-born inventors in US counties

	(1)	(2)	(3)	(4)
VARIABLES	ln Total Patents	ln Total Patents	ln Total Patents	ln Total Patents
Treated	2.271***	1.913***	1.913***	1.711***
	(0.000)	(0.000)	(0.000)	(0.000)

[4] [1- exp(-0.845)] * 100 = [1- 0.429] * 100 = 57% and [1- exp(-0.515)] * 100 = [1 – 0.59] * 100 = 41%

[5] [1- exp(-0.831)] * 100 = [1- 0.436] * 100 = 56% and [1 – exp(-0.505)] * 100 = [1 – 0.60] * 100 = 40%

Did	-0.831***	-0.784***	-0.784***	-0.505***
	(0.000)	(0.000)	(0.000)	(0.000)
shareese	0.041***	0.022***	0.022***	0.022***
	(0.000)	(0.000)	(0.000)	(0.000)
totpop_std	0.251***	0.241***	0.241***	0.246***
	(0.000)	(0.000)	(0.000)	(0.000)
area_std	-0.018***	-0.009	-0.009	-0.008
	(0.001)	(0.186)	(0.186)	(0.265)
cropval_std	0.089***	0.085***	0.085***	0.087***
	(0.000)	(0.000)	(0.000)	(0.000)
vegaval_std	0.023	0.006	0.006	0.005
	(0.412)	(0.741)	(0.741)	(0.804)
fruitval_std	0.002	-0.002	-0.002	-0.004
	(0.906)	(0.871)	(0.871)	(0.780)
Constant	0.304***	1.507***	1.507***	1.966***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	350,001	350,001	350,001	350,001
R-squared	0.309	0.435	0.435	0.463
Decade FE	YES	YES	YES	YES
Tech FE	NO	YES	YES	YES
State FE	NO	YES	YES	YES
Decade#State FE	NO	NO	YES	YES
Decade#Tech FE	NO	NO	NO	YES

Robust pval in parentheses *** p<0.01, ** p<0.05, * p<0.1

Note: Difference in Differences on the effect of the quota restriction on Total Patents in its logarithmic form. The first column considers only Time FE; the second one, Technology, State and Time FE; the third one adds the State#Time interaction dummy, and the last column reports all the FE terms, including the interaction dummy Technology#Time FE; This model is calculated using the sample with only US-born total patents only.

6.2 Effect on breakthrough patents in US counties

To test the effect on breakthrough inventions we estimate the following linear probability model (LPM):

$$YBR_{rft} = \beta_0 + \beta_1(exposure_{rft} * post_t) + \beta_2 exposure_{rft} + \beta_3 post_t + X' + \varphi_r + \delta_t + \gamma_f + \lambda_{rt} + \theta_{rt,ft} + \varepsilon_{rft} \quad (2)$$

where the dependent variable YBR_{rft} is the likelihood that a county *r,* in a given technology *f,* in the decade *t* produces a breakthrough. YBR_{rft} takes value 1 if a patent is a breakthrough and 0 otherwise. The right hand side of equation 2 is the same as equation 1. The findings reported in Table 3 suggest that the quotas impacted also on the production of novel and impactful inventions, though the overall effect is less sizable than for total patents. After the introduction of the quotas, a breakthrough patent in a ESE region would be between 16,7% and 15,5% lower than in the control group (see Columns 1 to 4, Table 3).

Table 3: The effect of the Quota Act on the breakthrough inventions in US counties

	(1)	(2)	(3)	(4)
VARIABLES	Breakthroughs	Breakthroughs	Breakthroughs	Breakthroughs
Exposure	0.238***	0.226***	0.216***	0.216***
	(0.000)	(0.000)	(0.000)	(0.000)
Did	-0.167***	-0.164***	-0.157***	-0.155***
	(0.000)	(0.000)	(0.000)	(0.000)

shareese	0.004***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.001)	(0.001)
totpop_std	0.036***	0.034***	0.035***	0.035***
	(0.000)	(0.000)	(0.000)	(0.000)
area_std	-0.003***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.001)	(0.001)
cropval_std	-0.001	-0.000	-0.000	-0.000
	(0.271)	(0.781)	(0.984)	(0.986)
vegaval_std	0.004	0.002	0.002	0.002
	(0.122)	(0.188)	(0.218)	(0.218)
fruitval_std	0.004***	0.004***	0.003***	0.003***
	(0.001)	(0.001)	(0.006)	(0.006)
Constant	0.009***	0.069**	0.083*	0.092**
	(0.000)	(0.028)	(0.072)	(0.046)
Observations	350,001	350,001	350,001	350,001
R-squared	0.159	0.186	0.188	0.193
Decade FE	YES	NO	YES	YES
Tech FE	NO	YES	YES	YES
State FE	NO	NO	YES	YES
Decade#State FE	NO	NO	YES	YES
Decade#Tech FE	NO	NO	NO	YES

Robust pval in parentheses *** p<0.01, ** p<0.05, * p<0.1

Note: Difference in Differences on the effect of the quota restriction on the likelihood of counties-technologies producing breakthrough innovations. The first column considers only Time FE; the second one, Technology, State and Time FE; the third one adds the State#Time interaction dummy, and the last column reports all the FE terms, including the interaction dummy Technology#Time FE; This model is calculated using the sample with only US-born total patents namely patents produced by US-born and migrant inventors only.

We find that the quotas also affected the production of breakthroughs by US-born inventors. After 1924, US-born inventors in ESE regions were between 16,3% and 15,2% less likely to patent a breakthrough, as reported in Table 4, models 1 to 4. The results are robust to the introduction of fixed effects and interaction fixed effects (i.e. state-time and technology-time), as shown in columns 2, 3 and 4 in Tables 4.

Table 4: The Effect of the Quota Act on breakthroughs of US-born inventors in US counties

	(1)	(2)	(3)	(4)
VARIABLES	Breakthroughs	Breakthroughs	Breakthroughs	Breakthroughs
Exposure	0.233***	0.220***	0.212***	0.211***
	(0.000)	(0.000)	(0.000)	(0.000)
Did	-0.163***	-0.160***	-0.154***	-0.152***
	(0.000)	(0.000)	(0.000)	(0.000)
shareese	0.004***	0.002***	0.002***	0.002***
	(0.000)	(0.001)	(0.002)	(0.002)
totpop_std	0.036***	0.034***	0.035***	0.035***
	(0.000)	(0.000)	(0.000)	(0.000)
area_std	-0.003***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.001)	(0.001)
cropval_std	-0.001	-0.000	-0.000	-0.000
	(0.264)	(0.769)	(0.959)	(0.961)
vegaval_std	0.004	0.002	0.002	0.002

	(0.123)	(0.192)	(0.221)	(0.222)
fruitval_std	0.004***	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.007)	(0.007)
Constant	0.009***	0.068**	0.076	0.084*
	(0.000)	(0.026)	(0.101)	(0.067)
Observations	350,001	350,001	350,001	350,001
R-squared	0.158	0.185	0.187	0.192
Decade FE	YES	YES	YES	YES
Tech FE	NO	YES	YES	YES
State FE	NO	YES	YES	YES
Decade#State FE	NO	NO	YES	YES
Decade#Tech FE	NO	NO	NO	YES

Robust pval in parentheses *** p<0.01, ** p<0.05, * p<0.1

Note: Difference in Differences on the effect of the quota restriction on the likelihood of counties-technologies producing breakthrough innovations. The first column considers only Time FE; the second one, Technology, State and Time FE; the third one adds the State#Time interaction dummy, and the last column reports all the FE terms, including the interaction dummy Technology#Time FE; This model is calculated using the sample with only US-born total patents only.

6.3 Effect on technological classes in US counties

The loss of ESE inventors could also reduce patenting activity in a particular technology field to the point where it disappears from the region. To test whether technology fields have disappeared as a result of the Quota Acts, we estimate the following model:

$$Y_{rft} = \beta_0 + \beta_1\left(ESEregion_{rft} * post_t\right) + \beta_2 ESEregion_{rft} + \beta_3 post_t + X' + \varphi_r + \delta_t + \gamma_f + \lambda_{rt} + \theta_{rt,ft} + \varepsilon_{rft}$$
(3)

Where the dependent variable Y_{rft} is the probability that a patent is produced in a given county *r* and technology *f* in decade *t*. Y_{rft} takes value 1 if a pair county-technology produces a patent, and 0 otherwise. The right-hand side of equation 3 is the same as equations 1 and 2.

Table 5 below reports the results. We observe a decrease in patenting in certain technological fields: the likelihood of having a patent in a given technological class decreases between 18,5% and 9% after the Quota Act (see Columns 1 to 4).

Table 5: The effect of the Quota Act on technological classes in US counties

	(1)	(2)	(3)	(4)
VARIABLES	Prob(Y_{rft})	Prob(Y_{rft})	Prob(Y_{rft})	Prob(Y_{rft})
Exposure	0.376***	0.320***	0.295***	0.258***
	(0.000)	(0.000)	(0.000)	(0.000)
Did	-0.185***	-0.171***	-0.138***	-0.090**
	(0.000)	(0.000)	(0.000)	(0.011)
shareese	0.007***	0.004***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)
totpop_std	0.048***	0.046***	0.047***	0.047***
	(0.000)	(0.000)	(0.000)	(0.000)
area_std	-0.003***	-0.002*	-0.002*	-0.002*
	(0.000)	(0.051)	(0.092)	(0.092)
cropval_std	0.009***	0.009***	0.009***	0.009***
	(0.000)	(0.000)	(0.000)	(0.000)
vegaval_std	0.005	0.002	0.002	0.002
	(0.284)	(0.443)	(0.546)	(0.546)

fruitval_std	0.001	0.001	0.000	0.000
	(0.503)	(0.645)	(0.845)	(0.845)
Constant	0.029***	0.032***	0.033***	0.033***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	7,531,056	7,531,056	7,531,056	7,531,056
R-squared	0.116	0.179	0.182	0.198
Decade FE	YES	YES	YES	YES
Tech FE	NO	YES	YES	YES
State FE	NO	YES	YES	YES
Decade#State FE	NO	NO	YES	YES
Decade#Tech FE	NO	NO	NO	YES

Robust pval in parentheses *** p<0.01, ** p<0.05, * p<0.1

Note: we use 4-digit technologies and used an exposure measure of at least one ESE inventor in any county and technology.

6.4 Robustness checks

In this section, we present a series of robustness checks to test the stability of our findings. We first use alternative measures of "exposure" as discussed in section 5. The results of this exercise are qualitatively comparable with those reported in our baseline model in Tables 1, 2, 3 and 4. Interestingly, we notice that the estimates obtained using stricter exposure thresholds yield larger negative coefficients (see Tables E.1 and E.2 in the Appendix). As shown in columns 2 and 3 of Table E.1 in the appendix, the percentage of patenting activity fell by 71% and 83.1%, respectively[6] after the quota act. We also test the same thresholds for breakthrough inventions. In this case, the results are consistent with the baseline model, although the coefficient estimates are larger. Columns 2 and 3 of Table E.2 (see Appendix) show the estimates with the stricter thresholds. We find that breakthrough innovations decreased by 26% and 31% respectively.

Second, we use alternative econometric models. We test a panel data estimator with the same specifications of equations 1 and 2 (see Appendix F). The results are qualitatively similar to those of the baseline model. The coefficient estimates reported in column 1 of Table F.1show that the number of patents decreased by 144 units per county-technology on average. In column 2, the results on breakthroughs show that ESE regions had on average about 2.8 fewer patents. Second, we test a Poisson model to account for the large number of zeros. We find an average decrease in patenting of 8%[7] (see column 1 of Table F.2 in the Appendix). The same model was tested for breakthrough for US-born inventors. In this case we find that the inventive activity of the ESE regions decreases by a factor of almost 64% on average[8]. Finally, we test a logistic regression (see Table F.3). The results show that the number of breakthrough inventions decreases by between 17% and % when all FE terms[9] are added.

Third, we use two additional measures of the breakthrough variable. First, in the model shown in Table G.1 in the Appendix, we classify only patents in the top 5% of their year cohort as "breakthrough". This means that a breakthrough patent is novel at the 5% level of its year cohort and impactful at the 5% level of its year cohort. As we can see in Table G.1, our main results hold using this stricter definition. The estimates show that by US-born inventors in an ESE region would be 9% less likely to produce breakthrough innovations. Second,

[6] [1- exp(-1.213)]*100 = [1 – 0.29] * 100 = 71% and [1 – exp(-1.777)] * 100 = [1 - 0.169] * 100 = 83,1%.
[7] [1- exp(-0.083)] * 100 = [1- 0.92] * 100 = 8%
[8] [1- exp(-1.030)] * 100 = [1- 0.36] * 100 = 64%
[9] Probability = odds/ (1+ odds)

we use the measurements of Kelly et al. (2018) for the same sample of historical patents. As shown in Table G.2, after the quotas, a ESE region would be 14% less likely to produce a breakthrough innovation.

7. Conclusion

The quotas implemented in the US in 1921-1924 were designed to limit the arrival of unskilled workers from Italy, Poland and Russia, among other southern and eastern European countries. The economic rationale behind these and other similar restrictive immigration policies is based on the idea that a large influx of immigrants from culturally distant places would bring the traits of their home country's rotten institutions to the destination country, thus impoverishing it. However, there is no consensus on the empirical basis of this epidemiological model. While some works suggest that entry barriers are justified for high rates of migration (Collier, 2013), others point in the opposite direction, suggesting that the benefits of immigration would be greater than the potential costs (Clemens and Pritchett, 2019). Another recent stream of literature spanning economic geography and innovation studies emphasises the benefits of the diffusion of ideas, particularly those embodied by immigrants (Kerr, 2018; Morrison, 2023). A growing body of evidence suggests that immigrants, particularly the highly skilled, contribute significantly to the technological development of host countries (Kerr and Lincoln, 2010) and regions (Miguelez and Morrison, 2023). More recently, this literature has focused on the impact of restrictive immigration policies on innovation. The underlying argument is that barriers to mobility prevent firms, regions and countries from accessing the skills and talent they need, thereby limiting their rate of innovation (Choudhury et al, 2022; Moser and San, 2020).

Our work relates to these academic debates by investigating the impact of restrictive immigration policies on inventive activity in the age of mass migration. In contrast to works that have focused mainly on policies for high-skilled immigrants, our attention focuses on a restrictive policy that was intended to limit the arrival of unskilled workers. Our results show that this restrictive immigration policy had unintended consequences that ultimately harmed the US technological development. The decline in arrivals directly reduced the total number of post-quota patents produced in US counties. This decline was significantly greater in counties in which ESE inventors were active before the policy was introduced. In addition, the quotas had an indirect negative effect on US-born inventors, whose invention activity declined as much as that of all other US inventors. This latter finding also suggests that immigrant inventors did not displace natives.

The quota act also had a negative effect on novel and impactful innovations, which are supposed to be the most valuable. Both the direct and indirect negative effects are indeed confirmed when we look at breakthrough innovations, albeit to a lesser extent. Our evidence also indicates that the geographical effects of national immigration policies are not negligible. For the case of the Quota Act, regions where ESE inventors were most active were most affected as compared to other regions. These findings are in line with the literature suggestion that barrier to immigration can be detrimental and generate unintended effects. In particular, we complement the evidence of Moser and San (2020), who focused on the effect of the quota act on foreign scientists.

Overall, our empirical analysis points to the crucial role that immigration policies can play for innovation and technological progress at local level.

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1. APPENDIX

A. VARIABLES AND DESCRIPTIVE STATISTICS

Table A1: Definitions of the variables used

Variable	Definition
Total patents	The total number of regular patents aggregated by county-technology in a given decade. We include this variable in its logarithmic form.
breakthrough	Dummy that takes value 1 if the county-technology (CPC class) has a patent in the top 10% of the value distribution of patents in the year cohort. For the robustness checks, we restricted the definition of a breakthrough as the top 5% of each year-cohort, and we used the measure developed by Kelly et al. (2018). We also used the count number of total breakthrough innovations in a given county-technology-decade. Source: Google Patents.
Exposure	Dummy that takes value 1 if the county-technology had at least one inventor (>=1) who filled a patent from any Eastern-Southern European country. ESE inventors are inventors born or hold the nationality of Austria-Hungary, Italy, Russia, Poland, Greece, Spain, Portugal, European Turkey, Slovakia, Ukraine, Lithuania, Romania and Latvia. Source: Google Patents.
exposureNWE	Dummy that takes value 1 if the county-technology had at least one inventor that filled a patent from any Northern-Western European country. NWE inventors are inventors that were born or hold the nationality of: Great Britain (including Northern Ireland and the Republic of Ireland for periods beyond 1922), Germany, France, Sweden, Switzerland, Norway, Denmark, The Netherlands, Belgium and Finland. Source: Google Patents.
post	Dummy that takes value 1 if the decade is after the quotas (1930 or 1940). It takes value of 0 if the decades are 1910 or 1920.
did	The interaction term between exposure (exposureNWE) and post. It depicts the main independent variables for the Difference in Differences strategy.
share	Share of the total number of migrants in a specific county in a decade. Source: IPUMS
shareese	Share of the total number of Eastern and Southern European migrants in a specific county in a decade. Source: IPUMS
sharenwe	Share of total number of Northern and Western European migrants in a specific county in a decade. Source: IPUMS.
totpop_std	Number of the total population of a specific county in a given decade. The variable has been standardised.
area_std	Number of acres that depict the area of each county. The

	variable has been standardised.
cropval_std	Number representing the value of crops production of a given county in a decade. Source: IPUMS. The variable has been standardised.
fruitval_std	Number representing the value of fruits production of a given county in a decade. Source: IPUMS. The variable has been standardised.
vegaval_std	Number representing the value of vegetables production of a given county in a decade. Source: IPUMS. The variable has been standardised.
decade	Dummies for decades 1910-1940. Source: Google Patents.
tech	Dummies for 2 digit CPC technological classes. Source: Google Patents.
state	Dummies for the 50 US states. Source: Google Patents.

Tables A.2 and A.3 reports the descriptive statistics of the variables and a correlation matrix among the variables. It is worth noting that our dependent variables are somewhat correlated, as they represent the same values with alternative measures.

The variable "migrants" shows a strong positive correlation with the total number of patents. This might imply the geographical concentration of inventors in highly productive counties and particular technologies. This might also be a concern regarding migrants' self-selection in highly innovative places, but this concern is softened by the empirical strategy chosen per se.

Table A2. Descriptive Statistics

Variable	Obs	Mean	Std.Dev.	Min	Max
totpat	359000	3.341	44.031	0	9878
ln_tot1	359000	.276	.794	.01	9.198
br	359000	.016	.126	0	1
breakthrough	359000	.107	3.061	0	667
migrants	359000	.11	3.217	0	733
esemigrants	359000	.031	1.194	0	389
nwemigrants	359000	.068	2.061	0	694
totpop_std	352000	0	1	-.304	32.782
shareese	352000	1.32	2.651	0	34.313
area_std	351000	0	1	-.706	13.884
cropval_std	351000	0	1	-.873	18.301
vegaval_std	351000	0	1	-.302	60.495
fruitval_std	351000	0	1	-.141	38.063

Table A3. Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) totpat	1.000												
(2) ln_tot1	0.428	1.000											
(3) br	0.316	0.460	1.000										
(4) breakthrough	0.414	0.210	0.273	1.000									
(5) migrants	0.707	0.224	0.189	0.375	1.000								
(6) esemigrants	0.608	0.176	0.139	0.154	0.831	1.000							
(7) nwemigrants	0.663	0.217	0.188	0.467	0.928	0.593	1.000						
(8) totpop_std	0.486	0.444	0.355	0.251	0.281	0.246	0.257	1.000					
(9) shareese	0.185	0.317	0.213	0.101	0.137	0.122	0.125	0.359	1.000				
(10) area_std	-0.012	-0.013	-0.017	-0.008	-0.008	-0.009	-0.008	-0.031	0.099	1.000			
(11) cropval_std	0.066	0.205	0.080	0.027	0.024	0.013	0.023	0.133	0.060	0.040	1.000		
(12) vegaval_std	0.088	0.170	0.103	0.045	0.042	0.028	0.040	0.161	0.117	0.047	0.446	1.000	
(13) fruitval_std	0.069	0.128	0.085	0.040	0.031	0.014	0.027	0.145	0.078	0.154	0.494	0.180	1.000

Table A.4. Distribution of standard patents and breakthrough innovations by nationalities pre and post-quotas (excluding US-born patents).

	Nationality	Pre-Time	Breakthrough	Share Br	Total Patents	Share Tot Pat
1	GREAT BRITAIN	0	1484	0,317	41114	0,370
2	GERMANY	0	1274	0,272	21829	0,197
3	FRANCE	0	341	0,073	8227	0,074
4	AUSTRIA-HUNGARY	0	242	0,052	6619	0,060
5	SWEDEN	0	208	0,044	5199	0,047
6	SWITZERLAND	0	293	0,063	4203	0,038
7	RUSSIA	0	184	0,039	4099	0,037
8	ITALY	0	95	0,020	3543	0,032
9	CANADA	0	46	0,010	3249	0,029
10	NORWAY	0	129	0,028	2445	0,022
11	DENMARK	0	67	0,014	1815	0,016
12	JAPAN	0	87	0,019	1111	0,010

	Nationality	Post-Time	Breakthrough	Share Br	Total Patents	Share Tot Pat
1	GREAT BRITAIN	1	204	0,122	2878	0,295
2	GERMANY	1	873	0,521	2300	0,236
3	FRANCE	1	60	0,036	804	0,082
4	SWITZERLAND	1	346	0,206	756	0,078
5	SWEDEN	1	33	0,020	485	0,050
6	AUSTRIA-HUNGARY	1	21	0,013	387	0,040
7	ITALY	1	11	0,007	328	0,034
8	CANADA	1	15	0,009	314	0,032
9	RUSSIA	1	11	0,007	180	0,018
10	DENMARK	1	11	0,007	159	0,016
11	POLAND	1	8	0,005	142	0,015
12	NETHERLANDS	1	21	0,013	128	0,013

B. Calculation of Breakthrough Innovations: Process.

The procedure we took to calculate the cosine similarities is the same for breakthroughs, novel patents, and impactful patents. The vectorisation of the word is as follows:

a. First, we parsed all the descriptions of each patent, and then we created a data frame containing each patent in different rows. This data frame included the patent number, the year and the text containing the whole description of each patent;
b. Then, we pre-processed the texts in the data frame by removing Greek characters, symbols, roman numbers, repeated letters, a list of stopwords manually collected by Arts et al. (2021), and finally, the stopwords set available in the natural processing language toolkit (NLTK) in English;
c. We lemmatised the tokens (words) using Snowball stemmer, and then we removed the tokens with frequency one and those tokens with a higher frequency but only within the same patent (i.e., the same word, many times in a single document);
d. After this pre-processing, we created a new list with words frequency that helped us later to penalise or reward those words that were out of the normal distribution of frequency (i.e. either higher or lower frequency);
e. We then vectorised each patent in a sparse matrix where rows are each patent and all the possible word columns, using the "*Sklearn's CountVectorizer*" package.

f. We calculated the dot product between one row in the sparse matrix (1 patent) with patents from previous (forward) years (10-year windows in the standard version). Then, we took the average scores in terms of cosine similarity for that particular patent.
g. Then, we computed 1-backwards to obtain the "novelty" of each patent on a scale between 0 and 1. The closer to 1, the more novel the patent. We also computed the impact of each patent by dividing the forward on the backward similarity (forward/backwards) to obtain a coefficient between 0 and 1. The closer to 1 indicates that a patent is more similar to patents in the future than those in the past.
h. After getting all the impact and novel coefficients, we assigned a 1 to those patents in the 10% more novel and 10% more impact of their year cohort. If a patent gets a 1 in novelty and 1 in impactful, then we consider such a patent to be a breakthrough innovation.

To deal with such an amount of data and because of the computational power, we parallelised all the processes by experimenting with having a more stable operation of taking the data for one year and dividing that workload over multiple processors of patents into 2-digit technological classes (CPC) and their description.

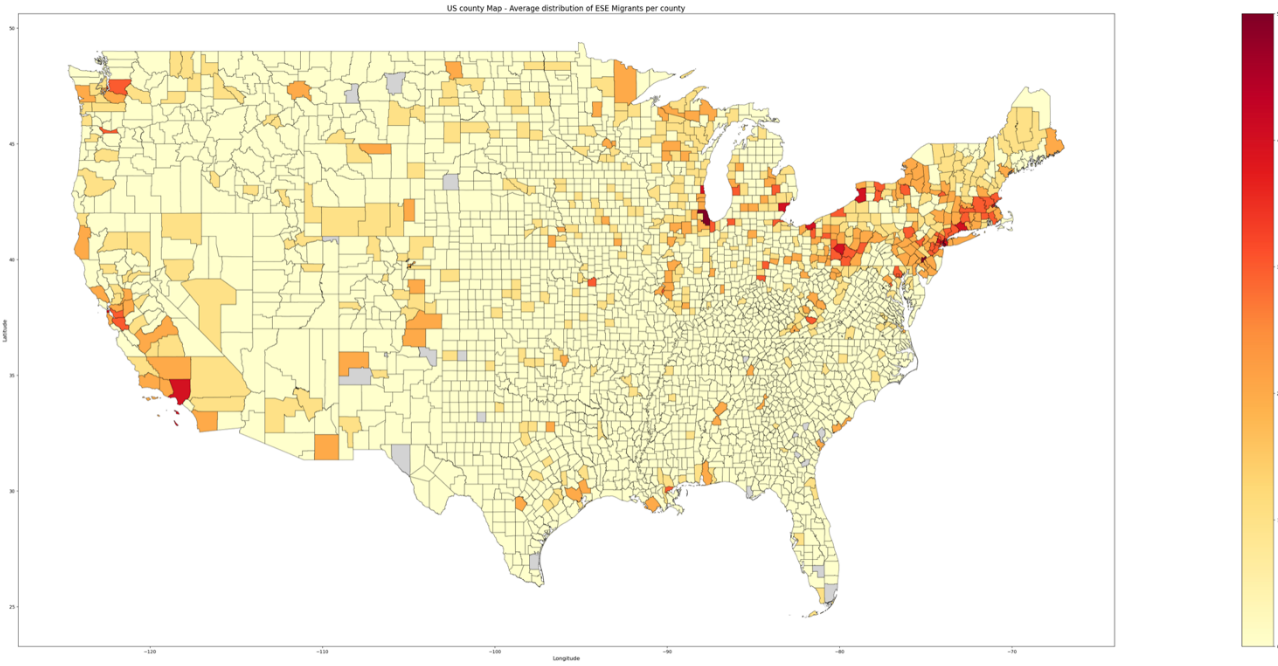
C. Table displays the aggregate patents and breakthroughs in the top 10% of the value distribution of patents invented in the same year cohort.

CPC	totpat	br 10%	Description	% br of totpat
C0	41301	11973	Chemistry, inorganic chemistry, explosives, fertilisers, organic chemistry, treatment of water and sewage, organic macromolecular compounds, dyes, polishes, adhesives, natural resins.	0,29
H0	105759	10844	Basic electric elements. Generation, conversion or distribution of electrical power. Basic electronic circuitry, electric communication techniques.	0,10
C1	25293	3428	Petroleum, Gas, or coke industry. Animal or vegetable oil. Biochemistry; microbiology, enzymology, genetic engineering. Beer, wines, sugar industry. Skins, pelts, leathers.	0,14
B6	330815	3127	Transporting	0,01
C2	18047	3011	Metallurgy	0,17
G0	105451	2811	Instruments: measuring, testing. Optics, photography, cinematography, horology, computing, calculating, checking-devices, signalling.	0,03
B0	55767	1776	Separating and mixing of physical and chemical materials.	0,03

D0	70392	1748	Textiles or flexible materials	0,02
B2	168827	1587	Shaping materials	0,01
F2	106091	1410	Lighting, heating	0,01
A2	26072	1133	Foodstuffs, tobacco	0,04
A4	169293	1124	Personal or domestic articles	0,01
A6	65082	1100	Health, amusement.	0,02
D2	7307	1002	Paper making, cellulose.	0,14
E0	138199	933	Building, constructions.	0,01
F0	70910	879	Engines or pumps.	0,01
B4	59138	638	Printing, typewriters, stamps.	0,01
A0	95123	617	Agriculture.	0,01
F1	115609	592	Engineering in general.	0,01
G1	19031	356	Musical instruments, acoustics, information storage, ICT for specific fields.	0,02
F4	15840	204	Weapons	0,01
B3	11854	133	Making articles with paper, layered products, additive manufacturing technologies.	0,01
E2	16389	46	Earth drilling, mining.	0,00
Y1	191	13	New technological developments	0,07
G2	167	12	Nucleonics	0,07
B8	111	7	Microstructural technology, Nanotechnology	0,06
C3	33	1	Crystal growth	0,03
D1	8	0	Related to textiles	0,00
Y0	1	0	New technological developments	0,00

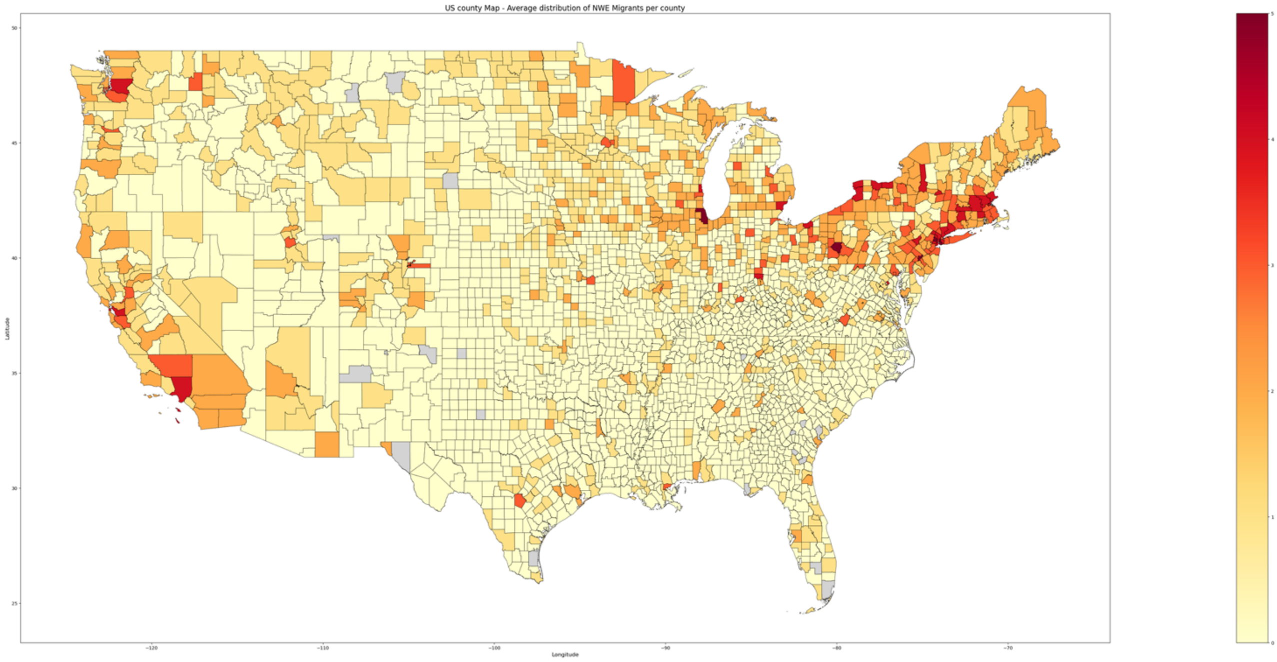
D- Maps showing the distribution of ESE and NWE migrant inventors in particular and ESE and NWE migrants in general.

Figure D.1: Average ESE Migrant Inventors in US counties.



Source: Plotted by authors.

Figure D.2: Average NWE Migrant Inventors in US counties.



Source: Plotted by authors.

Figure D.3: Average ESEs migrant distribution in US counties.

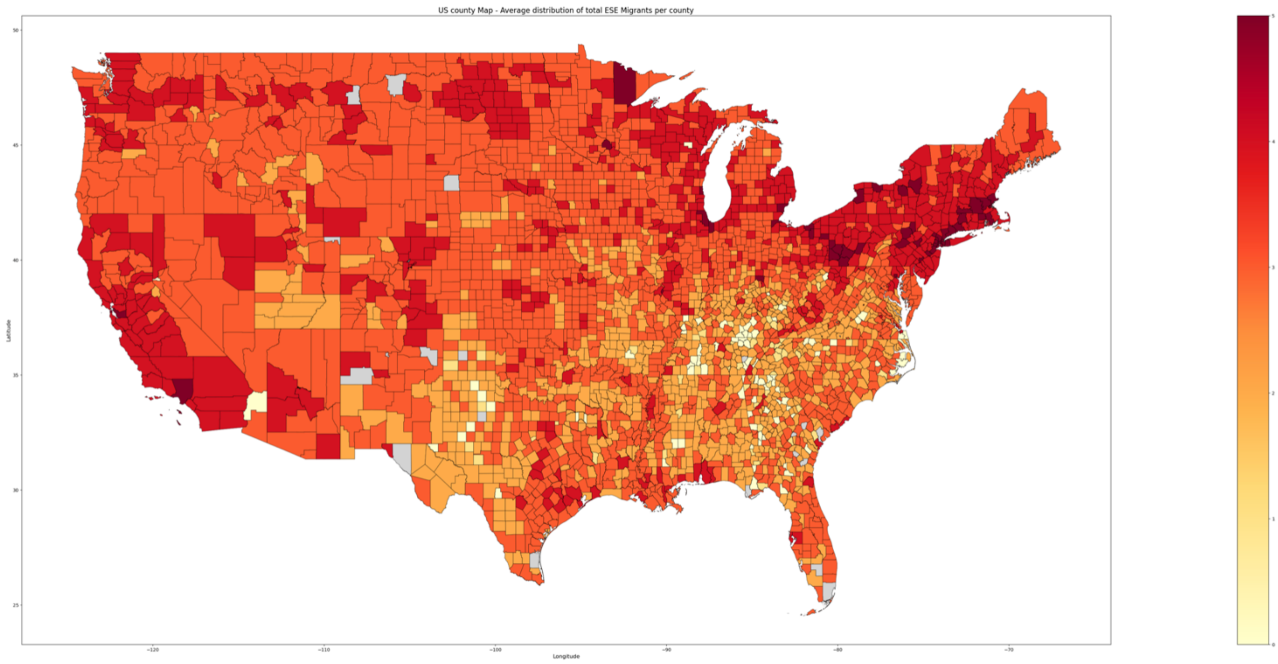
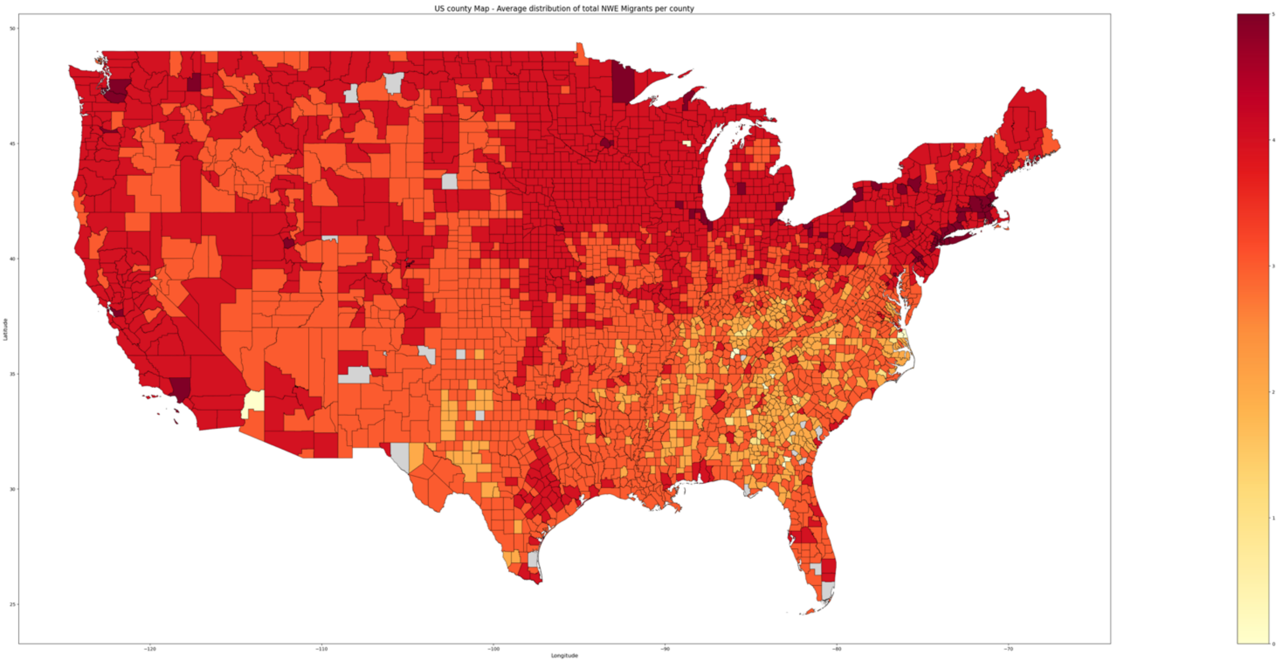


Figure D.4: Average NWEs migrant distribution in US counties.



E. Robustness checks: Different thresholds:

Table E.1: The Effect of the Quota Act on the Inventive Activity in US Counties
- Comparison of Different Thresholds

	Baseline	**ESE>1**	**ESE/NWE>1**
	(1)	(2)	(3)
VARIABLES	ln Total Patents	ln Total Patents	ln Total Patents
Exposure	1.913***	2.316***	2.307***
	(0.000)	(0.000)	(0.000)
Did	-0.784***	-1.213***	-1.777***
	(0.000)	(0.000)	(0.000)
ESEmigrants			
Constant	1.507***	1.569***	1.448***
	(0.000)	(0.000)	(0.000)
Observations	350,001	350,001	350,001
R-squared	0.435	0.422	0.394
Control FE	YES	YES	YES
Decade FE	YES	YES	YES
Tech FE	YES	YES	YES

State FE	YES	YES	YES

Robust pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table E.2: **The Effect of the Quota Act on the Breakthrough Inventions in US Counties**
- Comparison of Different Thresholds

	Baseline	**ESE>1**	**ESE/NWE>1**	**Continuous**
	(1)	(2)	(3)	(4)
VARIABLES	Breakthroughs	Breakthroughs	Breakthroughs	Breakthroughs
Exposure	0.220***	0.310***	0.280***	
	(0.000)	(0.000)	(0.000)	
Did	-0.160***	-0.257***	-0.313***	-0.011***
	(0.000)	(0.000)	(0.004)	(0.006)
ESEmigrants				0.006**
				(0.041)
Constant	0.068**	0.075**	0.075**	0.079**
	(0.026)	(0.017)	(0.018)	(0.018)
Observations	350,001	350,001	350,001	350,001
R-squared	0.185	0.182	0.170	0.169
Control FE	YES	YES	YES	YES
Decade FE	YES	YES	YES	YES
Tech FE	YES	YES	YES	YES
State FE	YES	YES	YES	YES

Robust pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

F- Robustness Checks: Different Econometric Models

Table F.1: Panel Data Model

	(1)	(2)
VARIABLES	Total Patents	Breakthroughs
Exposure	73.721***	2.419***
	(0.000)	(0.000)
Did	-144.530***	-2.864**
	(0.001)	(0.047)
time	-0.951**	0.014
	(0.020)	(0.329)
Constant	1.319	0.005
	(0.200)	(0.910)
Observations	350,001	350,001
R-squared	0.079	0.010
Number of id	89,059	89,059
Controls	YES	YES
FE	YES	YES

Robust pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Differences on the effect of the quota restriction on Total Patents and on Total Breakthrough Innovations using a panel regression model.The results show the effect of the quotas on the production of total standard and breakthrough patents by US-born inventors only.

Table F.2: Panel model using Poisson

VARIABLES	(1) Total Patents	(2) Breakthroughs
Exposure	0.164***	1.015***
	(0.000)	(0.000)
Did	-0.083**	-1.030***
	(0.044)	(0.000)
time	-0.650***	0.723***
	(0.000)	(0.000)
Observations	152,769	14,234
Number of id	38,490	3,571
Controls	Yes	Yes
FE	YES	YES

Robust pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Difference in Differences on the Effect of the Quota Restrictions on Total Patents (column 1) and Total Breakthrough Innovations (column 2), using a Poisson model to account for the nature of each dependent variable. The results show the effect of the quotas on the production of total standard and breakthrough patents.

Table F.3: Non-Linear Probability Model - Logit

VARIABLES	(1) Breakthroughs	(2) Breakthroughs	(3) Breakthroughs	(4) Breakthroughs
Exposure	1.981***	1.245***	1.312***	1.106***
	(0.000)	(0.000)	(0.000)	(0.000)
Did	-1.552***	-2.156***	-2.254***	-2.086***
	(0.001)	(0.000)	(0.000)	(0.000)
Constant	-4.849***	-3.644***	-3.356***	-2.738***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	350,001	325,863	321,786	295,232
Controls	YES	YES	YES	YES
Decade FE	YES	YES	YES	YES
Tech FE	NO	YES	YES	YES
State FE	NO	YES	YES	YES
Decade#State FE	NO	NO	YES	YES
Decade#Tech	NO	NO	NO	YES
Pseudo R-squared	0.215	0.373	0.376	0.393

Robust pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Logistic regression on the effect of the quota restriction on the likelihood of a Breakthrough Innovation. The results show the effect of the quotas on the likelihood of a county-technology to producing a breakthrough patents by US-born inventors only.

G- Robustness Checks: Different Measurements Of Breakthrough Innovations

Table G.1: The Effect of the Quota Act on the Breakthrough Inventions in US Counties at the Top 5% of each year cohort

	(1)
VARIABLES	Breakthrough 5%
treated	0.135***
	(0.000)
did	-0.092***
	(0.000)
time	0.000
	(0.399)
Constant	0.022
	(0.186)
Observations	350,001
R-squared	0.146
Controls	YES
Decade FE	YES
Tech FE	YES
State FE	YES

Robust pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Difference in Differences on the effect of the quota restriction on the likelihood of a county-technology producing Breakthrough Innovations restricting the sample to the top 5% breakthrough innovation per year cohort. The results show the effect of the quotas on the likelihood of a county producing breakthrough patents by US-born inventors only.

Table G.2: The Effect of the Quota Act on the Breakthrough Inventions in US Counties (Kelly et al. , 2021 measurement)

	(1)
VARIABLES	Breakthroughs Kelly et al.
treated	0.287***
	(0.000)
did	-0.139***
	(0.000)
time	-0.014***
	(0.000)
Constant	0.093***
	(0.001)
Observations	350,001
R-squared	0.188
Controls	YES
Decade FE	YES
Tech FE	YES
State FE	YES

Robust pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Difference in Differences on the effect of the quota restriction on the likelihood of a county-technology producing Breakthrough Innovations using the measurement developed by Kelly et al. (2021). The results show the effect of the quotas on the likelihood of a county producing breakthrough patents by US-born inventors only.