Immigration and Invention:

Evidence from the Quota Acts

Kirk Doran   Chungeun Yoon

University of Notre Dame

Abstract

Since (Hicks, 1932), economists have noted that inventions often economize on labor, so scarce labor should encourage more invention. But (Acemoglu, 2010) notes that in canonical macroeconmic models, plentiful labor encourages invention. The stakes of this debate are high in the policy context of mass immigration. We provide the first causal evidence of the effect of mass immigration on invention, using variation induced by 1920s quotas, which ended history's largest international migration to the U.S.. Inventors in cities exposed to fewer low-skilled immigrants applied for fewer patents, an effect driven by fewer patent applications relevant for the industries that lost the most immigrant workers.

We thank George Borjas, Brian Cadena, Bill Evans, Ina Ganguli, Daniel Hungerman, Joseph Kaboski, Shu Kahn, Bill Kerr, Ethan Lieber, Francesco Lissoni, Megan MacGarvie, Gabriele Pellegrino, Sergio Petralia, Reinhilde Veugelers, Abigail Wozniak, and seminar participants at the NBER and the GEOINNO2018 Conference. We thank Grace Enright and Cody Kankel for excellent research assistance. All errors are our own.

I Introduction

Since Hicks (1932), economists have posited that scarce factors of production will encourage inventions that economize on the scarce factor. The famous Habakkuk hypothesis (Habakkuk, 1962; Acemoglu, 2010) applied this argument to the first Industrial Revolution, positing that relatively scarce labor in early nineteenth century America incentivized more laborsaving inventions in America than in England. But the theoretical results in (Acemoglu, 2010) show that in general equilibrium, contrary to Hicks and Habakkuk, plentiful labor supply will encourage invention in the context of canonical macroeconomic models. This long-running debate is not only theoretical; it intersects with a policy question of perennial concern: how will mass migration affect the innovativeness of a society, and thus long-term economic growth? On the one hand, under the Hicks/Habakkuk hypothesis mass migration will reduce labor scarcity and thereby reduce the incentive to invent. On the other hand, under the Acemoglu general equilibrium results, mass migration will reduce labor scarcity and thereby increase the incentive to invent. In spite of the importance of this question to both economic theory and policy, the causal empirical literature relating immigration to innovation has not addressed it.[1] It has been difficult to find a natural experiment that could reveal the effects of truly mass immigration on innovation. In this paper, we introduce the first causal evidence relating mass immigration to innovation.

In order to fill in this gap in the literature, we need a shock to mass immigration that is large enough to affect overall labor supply and extends over time for long enough to affect a long-term process such as invention. Furthermore, the shock must vary across a sufficient number of cities and industries to allow sufficient statistical power to detect changes in rare events such as patenting. Finally,

[1]Previous empirical studies have focused on the effect of small numbers of highly skilled immigrants on innovation, in part because of data availability, and in part because innovation is an inherently social and reciprocal phenomenon among highly skilled peers (Lucas, 2009). See Kerr and Lincoln (2010), Borjas and Doran (2012), Moser, Voena, and Waldinger (2014), Borjas and Doran (2015), and Borjas, Doran, and Shen (2018).

the shock to immigration must be unrelated to changes in the domestic demand for labor across cities and industries over time. The closing of America's borders to Southern and Eastern Europe brought about by the Quotas of 1921 and 1924 can satisfy all of these conditions. Abramitzky and Boustan (2017) suggest making use of these quotas, the largest policy reductions of the largest international migration in human history, to estimate the effect of mass immigration on economic outcomes. In the last two years, numerous studies have applied versions of the identification strategy of Ager and Hansen (2018) and Xie (2017) in order to estimate various geographically localized economic effects of mass immigration through the policy shock of the quotas.[2] The Ager and Hansen (2018) and Xie (2017) identification strategy is based on variation over time in the enactment of the quotas coupled with variation across locations in the quotas' impact. The quotas targeted immigration from Southern and Eastern Europe, while seeking continued immigration from Northern and Western Europe. America went from nearly open borders with Europe to a reduction in Italian Immigration of over 90%; at the same time, immigration from Scandinavia decreased by only 18%.

Because there is history dependence in which specific cities immigrants from specific source countries tend to choose (Card, 2001), the quotas disproportionately decreased immigration inflows to cities that had tended to receive immigrants from Southern and Eastern Europe before the quotas. As a result, we can learn the impacts of a reduction of immigrant inflows to a city by comparing cities with high Southern and Eastern European immigrant inflows before the quotas with otherwise similar cities with high Northern and Western European

[2]None of the seven papers in this burgeoning literature address the question of how mass migration affects innovation. Rather, they explore the effects of the quotas on: migration (Greenwood and Ward, 2015; Massey, 2016; Ward, 2017); population size, fertility, occupational sorting, and manufacturing productivity (Ager and Hansen, 2018); native migration and investment in human capital (Abramitzky and Boustan, 2017); government spending and politics (Tabellini, 2017); and manufacturing wages and migration (Xie, 2017). In 2017 and early 2018, we presented similar preliminary results to those reported in this paper, using a similar strategy, before we became aware of the existence of nearly contemporaneous but in fact prior papers using the quotas to estimate the effect of mass immigration on other, complementary outcomes. Here, for comparability with the prior literature, we operationalize our identification strategy on the "missing immigrant" calculations in Ager and Hansen (2018) and Xie (2017), although our results are robust to any of the small variations in strategy in the existing literature.

immigrant inflows before the quotas.

We apply a version of this identification strategy across both locations and industries in order to address our question of interest through a novel merge of newly released data. We measure outcomes for treated and comparison cities through complete count U.S. Census data with names from the 1920 U.S. Census, merged at the individual person level to all U.S. Patents from 1899 to the present from the PATSTAT database. Our patents-census merge comes from Doran (2018), with the matching procedure explained in more detail in the Data section below. We supplement this matched data with Census data from the 1910 and 1930 Censuses as well. Using this data, we identify both cities and industries that were highly exposed to the Quotas, and apply both standard difference-in-differences and event study methods as well as the synthetic control method of Abadie, Diamond, and Hainmueller (2010) to compare the exposed cities and industries with otherwise similar comparison cities and industries.

In cities where the quotas reduced the inflow of immigrants, incumbent inventors reduced their number of patent applications per year compared to what they would have produced based on their previous patenting profiles or based on the patenting profiles of otherwise similar inventors in otherwise similar but less affected cities. For every ten percent reduction in new immigrants arriving in a city per year, inventors in that city reduced their patent applications by 0.5 percent per year. We also find similar reductions in citation-weighted patents, as well as the probability of becoming an inventor among people who had not already done so before the quotas.

Each patent application in our database is relevant to some industries but not others. It turns out that much of the reduction in innovation in quota-exposed cities arises because inventors living in these quota-exposed cities had been disproportionately applying for patents that were designed to be relevant for local, quota-exposed industries. In particular, we find that nearly all of the decline in patent applications by inventors living in quota-exposed cities can be explained by a decline in their inventions specifically relevant for local industries above the 75th percentile in their exposure to the quota; inventions relevant for non-quota-exposed industries do not significantly change.

This suggests that the mechanism in Acemoglu (2010) is at work: industries experienced reduced inflows of new immigrants as employees, causing local inventors who had specialized in providing the "strongly labor-complementary" inventions relevant for these industries to produce fewer such inventions, and hence fewer inventions overall.

Because the inventions characteristic of the era were all designed to provide more value for less labor, it can be difficult to imagine how the intuitive argument of Hicks/Habakkuk could be overturned here. A specific example can help shed light. Consider the dual clusters of inventions of the automated assembly line and the mass-producible automobile. These inventions were characteristic of the second industrial revolution, in that they used electric-powered machinery and interchangeable parts (the so-called "American system of manufacturing") to provide a new product through very low hours of labor per unit of output. In a casual sense, therefore, these were labor saving inventions, as were most of the famous inventions of the second industrial revolution in America. But, in fact, the usefulness of these inventions was not unrelated to scale. The new product and method of production made Henry Ford's automobile factory by necessity the largest production facility in the world, in which 3,000 parts needed to be combined through a total of 7,882 tasks. Given so many unique tasks, in order to take advantage of the full benefits of the division of labor, the new assembly line required 14,000 employees; the work was so repetitive (and thus turnover so rampant), that the actual number of employees required in a year was considerably higher.[3] The output totaled 300,000 automobiles a year, requiring a large consumer base to recoup costs. Thus, it is possible that, in general equilibrium, the inventions characteristic of America's second industrial revolution were only worthwhile to be produced in the context of both plentiful labor supply and con-

[3] See:(Beniger, 1997); Meyer (1981); and http://corporate.ford.com/innovation/100-years-moving-assembly-line.html (http://www.autolife.umd.umich.edu/Labor/L_Overview/L_Overview3.htm)

sumers.[4] The era of mass migration may have provided necessary fuel for the era of great American invention.[5]

We also empirically consider an alternative mechanism for our patenting results: that the constraints on invention in quota-affected cities increased, because low-skilled immigrants had been substituting for native time on non-innovative tasks, freeing up natives to spend time on innovation instead. Perhaps when the immigrant flows ceased, the cost of such substitution increased. Using our individual Census data on occupations, we do not find much support for this hypothesis.

Our results suggest that the literature's long focus on plentiful highly skilled immigrants and scarce low-skilled immigrants as leading drivers of domestic innovation may be misguided, at least from a historical perspective. The famous hypotheses of Hicks and Habbakuk do not find empirical support from the results of closing America's borders to mass inflows of the low skilled.

II Historical Context and Empirical Strategy

Between 1850 and 1920, over 30 million Europeans migrated to the United States (Abramitzky, Boustan, and Eriksson, 2014). As Figure 1a shows, at its peak, the annual inflow was over one and one half percent of the pre-existing U.S. population. Such a migration was unprecedented in size, and numerous economists and historians have analyzed its correlates and circumstances. As Figure 1b shows, Southern and Eastern Europeans comprised an increasing portion of the immigrants as the century progressed. Furthermore, the immigrants

[4] The natural experiments used in this paper are operationalized across locations and industries such that the treatment groups experience lower workforces than the comparison groups; both groups experience the loss in national consumer base for transportable goods. Thus, the effects reported in this paper are more likely to be due to labor scarcity, rather than the full effect in a general equilibrium setting of labor scarcity and a decline in consumer base combined.

[5] Indeed, this conclusion would be consistent with the literature relating the era of mass migration to changes in manufacturing and productivity during the second industrial revolution. Immigrants during this era may have encouraged mass production (Hirschman and Mogford, 2009), been complementary with assembly-line machinery (Lafortune, Tessada, and Lewis, 2015), and allowed for larger, more productive firms (Kim, 2007).

from Southern and Eastern Europe tended to be negatively selected by skill level (see Abramitzky and Boustan (2017) and Spitzer and Zimran (2014)).

American concerns about the effects of immigration grew in proportion to the increased prevalence of Southern and Eastern European immigrants shown in Figure 1b. Figure 1a demonstrates that World War I temporarily reduced immigration rates, but it took federal government policy to nearly end it. A literacy requirement established in 1917 over President Woodrow Wilson's veto was ineffective, but it was the 1921 Emergency Quota Act and the 1924 Immigration Act that effectively reduced immigration to considerably lower rates for the next four decades.

Remarkably, these quotas were precisely calibrated to leave immigration from Northern and Western European countries nearly constant, while nearly ending immigration from much of Southern and Eastern Europe. The precise calibration of the 1921 and 1924 Quotas is apparent through comparing pre-quota immigration from Scandinavia and Italy with the quotas for Scandinavia and Italy. The 1921 law set an annual quota of new immigrants from each nationality at two percent of the number of foreign-born persons of such nationality resident in the US in 1910. The 1924 law set an annual quota of each nationality at three percent of the number of foreign-born persons of such nationality resident in the US in 1890. The results of these calculations were startling. The 1921 Scandinavian immigration flow was 22,854. The post-1921 Scandinavian quota was 41,412. The 1921 Italian immigration flow was 222,260. The post-1921 Italian quota was 40,294. Thus, at the 1921 quota levels, immigration from Italy would still be twice the immigration from all of Scandinavia combined, because the Scandinavian quota was underutilized. It is not surprising, therefore, that the 1924 Quota used new calculations, to arrive at a Scandinavian quota of 18,665, and an Italian quota of only 3,845. The final 1924 quotas appear to have been carefully calibrated to keep immigration from some nations roughly constant, while nearly eliminating immigration from other nations. Table 1 reports the average quotas throughout the period, comparing them with actual immigration numbers from

Willcox et al. (1929) and U.S. Department of Commerce (1924, 1929, 1931).

In Figures 2a, 2b, and 3, we present a slightly modified replication of the results in Ager and Hansen (2018) which starkly demonstrates the effects of the quotas' careful calibration. We follow them in regressing actual immigration inflows from 1900 through 1913 on a simple quadratic in time and projecting forward; in our case performing the analysis twice, once for Southern and Eastern Europe and once for Northern and Western Europe. It is apparent that the actual quotas were strictly binding for Southern and Eastern Europe as a whole, and barely binding for Northern and Western Europe. Figure 3 shows clearly that the quotas resulted in a massive number of "missing" immigrants, nearly all of them from Southern and Eastern Europe.[6]

All of the papers in the recent literature on the quotas use identification strategies that take advantage of the fact that this variation in quotas across source countries induced variation across US locations. Following Abramitzky and Boustan (2017), we map in Figure 4a the share of population in each U.S. county in 1920 from Northern and Western Europe; in Figure 4b from Southern and Eastern Europe. Clearly, there is variation between and within regions of the United States in where immigrants from these different sources tended to settle. Due to history dependence in where immigrants tend to settle (Card, 2001; Moretti, 1999), these pre-quota patterns in immigrant source countries across U.S. locations induced variation in post-quota impacts across U.S. cities, providing the first source of identifying variation we use in this paper. We also expand on the existing literature by demonstrating similar history dependence in which industries immigrants tended to work in before the quotas, thus providing a second source of identifying variation. The identification strategy thus consists in comparing cities and industries that had experienced substantial inflows from Southern and Eastern Europe with otherwise similar locations and industries that had experienced substantial inflows from Northern and Western Europe,

[6] See Figures 1 and 2 of Ager and Hansen (2018), page 31 for the original Figures that we replicate in Figures 2a, 2b, and 3 of this paper.

before and after the quotas.

One concern with this identification strategy would be if the laws were passed with precisely these induced effects across American cities and industries in mind. A problem for the exclusion restriction implicit in the identification strategy would be a scenario in which senators and representatives from some U.S. locations and industries sought to decrease the economic potential of competing U.S. locations and industries by cutting off their supply of low skilled labor while preserving their own. Under this scenario, the identification strategy would confuse the effects of the quotas with the effects of a host of correlated political acts designed by powerful Senators and Representatives to help some U.S. locations and industries and harm others during the early 1920s.

Indeed, Goldin (1994) runs regressions on vote counts to argue that early and unsuccessful attempts in 1915 and 1917 to limit immigration were based in part on economic concerns about immigration in general. But the argument of Goldin (1994) is that the economic concerns were national, and that so many voters supported an immigration restriction precisely because native rural voters (who did not live near immigrant)s were concerned about the perceived plight of native workers in the cities. Furthermore, her work does not address the successful attempts to curtail immigration in the 1921 and 1924 Quotas, in which the votes were nearly unanimous (89% of votes cast in the House were in favor of the 1921 restriction; 99% of votes cast in the Senate were). Thus, the 1921 and 1924 Quotas represented national concerns that affected natives everywhere, and were not part of an organized campaign to promote the economic wellbeing of one location over another.

Finally, we can learn what these national concerns were by examining the historical record of the debate leading up to the passage of these laws. During the discussions on the 1924 restriction, senators and representatives from around the country repeatedly expressed concerns about the ethnic heritage of people from Southern and Eastern Europe, as well as their religious affiliation (i.e., Catholic or Jewish). At the same time, they extolled the ethnic heritage of people from

"Nordic" countries as well as people of Protestant background. For example, Representative Ira Hersey of Maine complained: "We have thrown open wide our gates and through them have come other alien races, of alien blood, from Asia and southern Europe ... with their strange and pagan rites, their babble of tongues." Senator Earl Michener of Michigan explained: "The Nordic People laid the foundations of society in America. They have builded this Republic, and nothing would be more unfair to them and their descendants than to turn over this Government and this land to those who had so little part in making us what we are." Senator Reed of Pennsylvania stated his goal to "maintain the racial preponderance of the basic strain on our people and thereby to stabilize the ethnic composition of the population." Representative William Vaile of Colorado stated: "What we do claim is that the Northern Europeans, and particularly Anglo-Saxons, made this country."[7]

Thus, far from local efforts to reduce all immigration to some locations but not others, these laws were national efforts to reduce all immigration from some sources but not others. As historian Robert Fleegler recounts, "during the 1924 congressional debate over immigration restriction ... the supporters of restriction espoused a conception of American identity that excluded eastern and southern European migrants. Only a small minority disagreed" (Fleegler, 2013).

In the next section, we describe the data that we use to analyze the impacts of these quota-related declines in mass immigration on American innovation.

III Data and Matching

Administrative data from Willcox et al. (1929) and U.S. Department of Commerce (1924, 1929, 1931) gives us exact immigration counts by source country and year. IPUMS full count Census data tell us characteristics by locations, industry and year of arrival in the United States in 1900, 1910, 1920, and 1930: total pop-

[7]Quotes are from "Ellis Island Nation: Immigration Policy and American Identity in the 20th Century" by Fleegler (2013).

ulation, foreign-born population, southern and eastern European foreign-born population, and northern and western European foreign-born population. Complete count Census data with names from 1920 tell us: full names, genders, birth years, birthplaces, arrival years, locations, and occupations of everyone living in the United States in 1919 (the year the 1920 Census took place). The European Patent Office's PATSTAT database tell us characteristics of each patent application granted by the United States Patent Office from 1899 to the present: inventor's full name, year of application, International Patent Classification (IPC), and number of citations.

The identification strategy depends on variation across locations, industries, and years. Thus, it is helpful to observe immigration inflows into locations and industries on a yearly basis if possible. The 1910, 1920, and 1930 United States Censuses report the nativity status, birth country, and year of arrival for every person living in the United States in 1909, 1919, and 1929, respectively. We can therefore use these three censuses to determine the exact initial location choice and industry choice of immigrants who arrived in 1909, 1919, and 1929.

This would provide us with two pre-quota years for immigration inflows across locations and industries, and one post-quota year for immigration inflows across locations and industries. A difference-in-differences strategy relies on the assumption that treated and comparison groups have similar levels and trends of relevant variables before the treatment begins. While two pre-quota years (1909 and 1919) are useful for establishing pre-quota trends, it would be helpful to have richer data to establish the pre-quota trends, as well as to establish the exact year when the trends diverge post-quota. To do so, we develop a proxy for the initial locations and industries of immigrants who arrived in the years between censuses. Our proxy uses information from the 1910, 1920, and 1930 censuses, assigning immigrants who arrived in year t to the city and industry they report living and working in in the census closest to year t. Thus, for immigrants who arrived in 1919, the proxy corresponds with the true (contemporaneously observed) observations of initial locations and industries of new 1919 arrivals gleaned from the

1920 census. For immigrants who arrived in 1925, the proxy corresponds with the circa-1929 locations and industries reported in the 1930 Census for immigrants who report first arriving in 1925.

While the proxy corresponds with the truth during Census years themselves, the proxy will diverge from the truth in the years between censuses in two ways: through movement within the United States between year t and the next Census year, and through return migration. Fortunately, we can test the accuracy of the proxy by comparing the proxy vectors of the number of 1919-arrival immigrants across locations and industries reported in the 1930 Census with the true (contemporaneously observed) vectors of the number of 1919-arrival immigrants across locations and industries reported in the 1920 Census. We find that the location proxy and the industry proxy have correlations of approximately 0.9 with their respective true vectors. We can also perform all of the analysis below ignoring the proxy and relying only on three observations of newly arrived immigrants in 1909, 1919, and 1929, as in the existing literature on the effects of the quotas.

To determine the effect of the quotas on inventors who lose geographically close immigrants, we need to know where inventors were living just before the quotas occurred. An inventor i is treated by the 1921 and 1924 quotas if he or she is living in a city with a large fraction of southern and eastern European immigrants in 1919, just before the quotas. Patent applications report locations of their inventors that are valid at the moment the patent application was filed. But the median number of patent applications conditional on ever patenting is one (Bell et al., 2017), so the vast majority of incumbent inventors living in any given city in 1919 would be unlikely to happen to apply for a patent (and thereby reveal their current location) in 1919. This means that using the location data embedded in 1919 patent applications would cause us to substantially underestimate the number of inventors living in each location.

Therefore, we merge patent data into census data at the individual person level. We can then know where all inventors subject to the matching criteria were living in 1919, regardless of whether they applied for a patent that year. Furthermore, we can also control for demographic characteristics which are proven determinants of the probability of invention (Bell et al., 2017), thus improving the precision of our estimates.

We use a match between the EPO's PATSTAT patent database and the complete count 1920 U.S. Census with names introduced in Doran (2018). A fuzzy matching procedure merges patents and publications at the individual-name level into the 1900, 1910, 1920, 1930, and 1940 complete-count U.S. Censuses with names. Each such Census can tell us how many people living in the US at the time of that Census had any given first name, middle name, and last name combination. In any given Census, almost half of the population is made up of people who are the only person in the country with their first name, middle name, and last name combination. In particular, in the 1920 US Census, 43% of the US population is made up of people with unique names. The fuzzy matching procedure accounts for common misspellings and assigns each patent to the person or persons with a matching name in the Census. We impose three restrictions to increase the probability of matches being correct. First, and most importantly, we only consider the 43% of the population with a unique name. Second, we only consider matching patent applications with an implied age at application between the ages of 18 and 80. Finally, in most regressions we restrict attention to patents matched between the years 1919 and 1929.

Given these restrictions, it is very likely that the resulting matched patents are correct. Given a person with a unique name in the 1920 Census (observed in 1919), we know that any patents applied for in the years 1919 through 1929 with that unique name must be either from that person, or from someone who immigrated to the United States with that person's unique name during those years. They could not be from someone born after 1919 with the same unique name, because any such person would be younger than 10 years old. They could not be from someone with the same name born before 1919 who died by 1919, because such a person would be dead. Thus, for the 43% of people in our sample restriction, and for the eleven years in our primary regressions, the matched patents should only be incorrect if there are transcription errors in the names recorded in the raw data or if a new immigrant arrived with the same full name and patented shortly after arrival.[8]

We will also make use of the full PATSTAT database, with no matching restrictions, below, in order to determine the effect of the quotas on inventions relevant to specific industries. To determine the effect of the quotas on inventions relevant for the NAICS industry classifications in the 1920 U.S. Census, we use an IPC to NACE concordance and a NACE to NAICS concordance. The IPC to NACE (the industry standard classification system used in the EU) concordance is available in the PATSTAT data. The U.S. Census Bureau provides the NAICS to NACE concordance. Using these two concordances, we assign each of the USPTO patent applications in each year to a weighted set of NAICS industry classifications. The IPC information becomes less prevalent in the PATSTAT data before 1919, thus our assignment of patents to industries begins for 1919 patent applications.

Given the data described above, we construct a treatment group of locations likely to be exposed to the effects of the quotas, a treatment group of incumbent inventors already living in such cities before the quotas, and a treatment group of industries whose workforces were likely to be exposed to the effects of the quotas.

In the 1920 U.S. Census, there are a total of 3030 locations that are either cities or non-city regions of a county. We follow the "missing immigrants" method in Ager and Hansen (2018) to assign the missing immigrants in Figure 3 to different locations over time. For each location, we calculate the quota exposure through the following equation:

$$QuotaExposure_c = \frac{100}{P_{c,1920}} \sum_{j=1}^{J} \left(\widehat{Immig}_{j,22-30} - Quota_{j,22-30} \right) \frac{FB_{jc,1920}}{FB_{j,1920}} \quad (1)$$

[8]It is also be possible to use raw patent data from the PATSTAT database to construct city-year level patents to be used in regressions without the benefit of individual demographic characteristics to control for. We are pursuing this alternative technique which does not require matching in our current extensions to this work.

where $\widehat{Immig}_{j,22-30}$ is the estimated average immigration inflows per year from country j during the post-quota years from 1922 and 1930 if the quota acts had not been enacted. The variable $QuotaExposure_c$ represents the average annual number of "missing" immigrants per-100-inhabitants in city c due to quotas (see Ager and Hansen (2018)). In most specifications, we use a continuous version of this variable, but in those in which we use a discontinuous version we choose as our treated locations the 312 locations with the highest quota exposure (these represent the top ninety percent of locations ranked by quota exposure). A total of 145,842 incumbent inventors were living in these treated cities as of 1919.

In the 1920 U.S. Census, there are a total of 146 industries; seventy of these industries report more patents in the industry-patent match described above. For each such industry, we calculate a measure of quota exposure analogous to that for locations above.

We report simple statistics based on these data in Table 2. It is apparent that the most quota-exposed locations not only experienced more Southern and Eastern European immigration than other locations before the quotas, but also experienced more immigration in general. If locations that attracted many immigrants before the quotas have different tendencies after the quotas than do locations that attracted few immigrants before the quotas, then the identification strategy will confuse these differing tendencies for the effect of the quotas themselves. It is therefore useful to find a subset of comparison cities that not only did not have high Southern and Eastern European immigration before the quotas but also did have high Northern and Eastern European immigration before the quotas.

We use the synthetic control method of Abadie, Diamond, and Hainmueller (2010) to select comparison locations and industries that had similarly high levels of immigration to the treated cities before the quotas, but whose immigrants arrived from Northern and Western Europe instead. We establish a selection pool of 2718 locations with low quota exposures. We then select based on the following criteria: total population in 1910; foreign-born population 1910; average patents per year between 1915 and 1921; and the number of immigrants with arrival years 1905, 1910, 1913, 1917, and 1921 as a fraction of the location's 1910 total population. The selection criteria represent a tradeoff between selecting more exhaustively for pre-quota characteristics, versus demanding too much from the numerical algorithm in the Abadie, Diamond, and Hainmueller (2010) code; the results we report below are not sensitive to modifications in the selection criteria.

In order to use the synthetic control locations and industries as comparison groups in the regressions below, we must modify their weights to take into account the varying number of individual inventors living in each location before the quota. We do so with the following weights:

$$weight_j = \sum_{q=1}^{Q} \frac{w_j^q}{p_j} \cdot \frac{p_q}{\sum_q p} \tag{2}$$

where w_j^q is the raw value of weights from the synthetic control method for treatment city q and control city j, and p is the number of individuals in a given city. We report the unweighted and weighted simple statistics in the final two columns of Table 2. It is apparent that the weighted synthetic control locations more closely mirror the immigration rates of the treated cities before the quotas.

In the next section, we determine the effects of the quotas on immigration rates, labor force, and population size in quota-exposed locations and industries.

IV The Effects of the Quotas on Immigration Rates, Labor Force, and Population Size

We begin our analysis by verifying that the Quotas decreased immigration rates in quota-exposed locations and industries, decreased the labor force in quota-exposed locations and industries, and decreased the population size in quota-exposed locations.

We estimate difference-in-differences specifications of the following form:

$$Y_{ct} = \alpha + \beta(QuotaExposure_c \times PostTreatment_t) + \tau_t + \gamma_c + \epsilon_{ct} \qquad (3)$$

In Table 3, we report the results when the outcome variable is newly arrived immigrant inflows (rescaled by the 1910 population) in a given location in a given year, proxied for the years between censuses by the technique described in the Data section above. It is apparent that regardless of the years included in the sample, the cutoff year chosen for the beginning of the quotas, or the base year to rescale the immigration rates, the quotas resulted in substantial reductions of immigration inflows relative to pre-quota means.

In Figure 5, we report the proxied inflows of southern and Eastern European immigrants by year into highly treated locations (those with quota-exposures above the 90th percentile) versus comparison locations. It is apparent that a relative decline in immigration inflows occurred immediately after the 1921 and 1924 quotas. It is also clear that this relative decline was not the result of differential pre-quota trends. However, it is possible that the results have been affected by the fact that the comparison cities had very low levels of immigration before the quotas; there may be something else about such cities that caused differential post-quota trends after the quota.

To adjust for this possibility, we make use of the synthetic control locations described in the Data section above. In Figure 6a, we report the gaps in the fraction of new immigrants arriving each year between treated and synthetic control locations. It is apparent that even when comparing treated cities with comparison cities that had similar levels of immigration flows before the quotas, the quotas differentially affected the treated cities through cutting off their flow of southern and eastern European immigrants, thus decreasing their immigration flows overall relative to the counterfactual. We can also create placebo treatment cities with low levels of the quota exposure variable and compare them to their own synthetic controls, reporting the results in Figure 6b. Comparing the results in Figure 6c, it is clear that locations with high levels of quota-exposure had large decreases in their immigration inflows after the quotas, while locations with low levels of quota-exposure had much smaller decreases.

In Table 4, we report the results using the characteristics of the locations during the 1910, 1920, and 1930 Censuses. We modify equation (3) above slightly by taking first differences within locations before the quotas and first differences within locations after the quotas, and reporting the results separately. It is apparent that there were substantial declines in southern and eastern European populations, foreign-born populations, and total populations after the quotas. These declines are clearly not the result of pre-quota trends. The same holds true when we restrict attention to southern and eastern European workers, foreign-born workers, and total workers. In Figures 9, 10, and 11, we display graphically the results reported in Panel A of Table 4. Greater quota exposure is only associated with declines after the quotas, not before it.

In the next section, we determine how the quotas, which reduced populations and labor forces in affected cities, affected innovation as measured by patents and patent citations.

V The Effect of Immigration on Geographically Close Inventors

We estimate difference-in-differences specifications on incumbent native-born inventors of the following form:

$$Y_{ict} = \alpha + \beta(QuotaExposure_c \times PostTreatment_t) + \theta X_{it} + \tau_t + \gamma_i + \epsilon_{ict} \quad (4)$$

where Y_{ict} is the number of patents or citations of incumbent inventor i in city c and year t. We includes the quartic of age of person i in year t, the individual fixed effect, and the year fixed effect. We report the results from this estimation in Table 5. Clearly, regardless of the sample restrictions, years covered, or cutoff year for the post-quota period, we find large declines in the number of patents applied for per year by incumbent inventors living in quota-exposed locations. The magnitudes are large, but not implausible: an increase in quota exposure from 0 to 1 decreases patent applications per year by 5%. According to the results in Table 3, the equivalent increase in quota exposure decreases immigration inflows by 100%, while the results in Table 4 show that the equivalent increase in quota exposure decreases the overall number of employed individuals by as much as 3%. Thus, we find that for every 10% decrease in immigration, patent applications by incumbent native-born inventors decrease by 0.5%.

We compare the patent applications of inventors living in locations whose quota-exposure was greater than the 90th percentile compared with inventors living in other locations in Figure 7a and Figure 7b. It is clear from the timing of the trend break that the results are not an artifact of pre-quota differential trends. Note that because the analysis restricts itself to incumbent native-born inventors, the results are also not an artifact of differing probabilities of invention across native-born and immigrants, nor are they a direct artifact of differing selection of immigrant inventors on ability after the quotas. Finally, the results are also not a mere artifact of the differences in pre-quota levels of immigration across treated and comparison cities apparent in Figure 5. Using the synthetic control weights described in the Data section, we report reweighted versions of equation (4) in Table 6. It is apparent that the results are nearly identical: quota-related decreases in immigration were associated with substantial declines in patent applications by incumbent native-born inventors.

It is possible that the marginal inventions were not useful ones; perhaps the inventors would have invented the most useful inventions anyway, regardless of the shock of the quotas. To examine this possibility, we reestimate the results in Table 5 with citation-weighted patents as the outcome variable. It is evident that the results are very similar in sign, significance, and magnitude. Thus, incumbent inventors did not merely neglect their least successful patent applications; weighted by its later influence, native invention substantially declined.

The graphical results reported in Figure 8 demonstrate that these results are also not an artifact of differential pre-quota trends.

In the next section, we explore two possible mechanisms for this decline.

VI The Effect of Industry Labor Supply on Relevant Inventions

One possible mechanism for the results above is one inspired by Acemoglu (2010). It is possible that the equilibrium quantity of "strongly labor-complementary" inventions is lower in an industry in which labor is scarce compared with an industry in which labor is plentiful. If many incumbent inventors had been used to supplying strongly labor-complementary inventions to quota-exposed local industries before the quotas, then it is possible that decreased incentives to do so after the quotas decreased their overall rates of invention.

To test this hypothesis, we first determine whether some industries were more exposed to the quotas than others. We estimate the following equation at the industry-year level:

$$Y_{jt} = \alpha + \beta(QuotaExposure_j \times PostTreatment_t) + \tau_t + \gamma_j + \epsilon_{jt} \tag{5}$$

where Y_{jt} is the number of newly arrived immigrants per year into industry j rescaled by 1920 total workers in that industry j. We report the results of this estimation in Table 8. While the sample size is limited, it appears that there was a decline in the inflows of immigrant workers into industries that were more exposed to the quota after the quotas.

Thus, if the hypothesis above was at work, these quota-exposed industries should have demanded fewer inventions after the quota than they had before. Using the assignment of patents to relevant industries described in the Data section, we reestimate equation (4) and report the results in Table 9. It is apparent that nearly all of the reduction in patent applications reported in Table 5 was due to a reduction in applications relevant for highly quota-exposed industries (those with quota-exposure above the 75th percentile). Patent applications relevant for non-highly quota-exposed industries did not significantly change.

These results suggest that what declined substantially after the quotas was the invention of technology relevant for industries that lost workers due to the quotas. In these industries, labor became scarce, and this discouraged particular types of invention. In the context of Acemoglu (2010), this suggests that much of the invention at the time was "strongly labor-complementary".

An alternative hypothesis is that before the quotas immigrants may have disproportionately taken occupations that freed up native time for invention instead. After the quotas, natives would have to spend time that otherwise would have been spent inventing doing tasks immigrants had formerly done. Indeed, there is evidence that low skilled immigrants free high skilled women's time in general, although the evidence does not address invention in particular (see Cortes and Tessada (2011) and Cortes and Pan (2013)). To consider this hypothesis, we examine the fraction of each occupation in the 1920 Census held by the foreign-born, as well as the specifically southern and eastern European foreign-born. We do not find that occupations related to household-help were especially filled by either group.

VII Conclusion

In this paper, we provide the first causal evidence on the effect of mass immigration on U.S. inventors. We do so at the end of the largest international migration in history, during the tail end of America's second Industrial Revolution. Our results suggest that a ten percent reduction in mostly low-skilled immigration results in a 0.5 percent reduction in the number of patent applications by incumbent U.S. inventors. The results are not an artifact of a changing pool of inventors, differential pre-quota trends, or the loss of uncited patent applications.

The results seem to be driven by inventors who had specialized in providing "strongly labor complementary" inventions (Acemoglu, 2010) for local industries. Assigning each patent to its' relevant industries, we find that nearly all of the decline occurred among the subset of patents relevant for the industries whose workforces were most exposed to declining immigrant flows after the quotas.

Because inventions in general, and the inventions of the second industrial revolution in particular, are often designed to economize on labor, it is intuitive that making labor less plentiful should increase the incentive to invent. Since the work of Sir John Hicks (1932) and Sir John Habakkuk (1962), this intuition has suggested that America's early labor scarcity promoted its early technological development. Building off of the general equilibrium results of (Acemoglu, 2010), our paper suggests that at least during the golden age of American invention, it was plentiful labor that made invention worthwhile.

From a historical perspective, therefore, it appears that it was not necessity that was the mother of invention, but rather opportunity.

References

Abadie, A., A. Diamond, and J. Hainmueller (2010). Synthetic control methods for comparative case studies: Estimating the effect of california's tobacco control program. *Journal of the American statistical Association 105*(490), 493–505.

Abramitzky, R. and L. Boustan (2017). Immigration in american economic history. *Journal of Economic Literature 55*(4), 1311–45.

Abramitzky, R., L. P. Boustan, and K. Eriksson (2014). A nation of immigrants: Assimilation and economic outcomes in the age of mass migration. *Journal of Political Economy 122*(3), 467–506.

Acemoglu, D. (2010). When does labor scarcity encourage innovation? *Journal of Political Economy 118*(6), 1037–1078.

Ager, P. and C. W. Hansen (2018). Closing heaven's door: Evidence from the 1920s us immigration quota acts.

Bell, A. M., R. Chetty, X. Jaravel, N. Petkova, and J. Van Reenen (2017). Who becomes an inventor in america? the importance of exposure to innovation. Technical report, National Bureau of Economic Research.

Beniger, J. R. (1997). *The Control Revolution: Technological and Economic Origins of the Information Society*. Harvard University Press.

Borjas, G. J. and K. B. Doran (2012). The collapse of the soviet union and the productivity of american mathematicians. *The Quarterly Journal of Economics 127*(3), 1143–1203.

Borjas, G. J. and K. B. Doran (2015). Cognitive mobility: Labor market responses to supply shocks in the space of ideas. *Journal of Labor Economics 33*(S1), S109–S145.

Borjas, G. J., K. B. Doran, and Y. Shen (2018). Ethnic complementarities after the opening of china: How chinese graduate students affected the productivity of their advisors. *Journal of Human Resources 53*, 1–31.

Card, D. (2001). Immigrant inflows, native outflows, and the local labor market impacts of higher immigration. *Journal of Labor Economics 19*(1), 22–64.

Cortes, P. and J. Pan (2013). Outsourcing household production: Foreign domestic workers and native labor supply in hong kong. *Journal of Labor Economics 31*(2), 327–371.

Cortes, P. and J. Tessada (2011). Low-skilled immigration and the labor supply of highly skilled women. *American Economic Journal: Applied Economics 3*(3), 88–123.

Fleegler, R. L. (2013). *Ellis Island nation: Immigration policy and American identity in the twentieth century*. University of Pennsylvania Press.

Goldin, C. (1994). The political economy of immigration restriction in the united states, 1890 to 1921. In *The regulated economy: A historical approach to political economy*, pp. 223–258. University of Chicago Press.

Greenwood, M. J. and Z. Ward (2015). Immigration quotas, world war i, and emigrant flows from the united states in the early 20th century. *Explorations in Economic History 55*, 76–96.

Habakkuk, H. J. (1962). *American and British Technology in the Nineteenth Century: The search for labour saving inventions*. Cambridge University Press.

Hicks, J. R. (1932). *The Theory of Wages (2nd ed.)*. London: Macmillan.

Hirschman, C. and E. Mogford (2009). Immigration and the american industrial revolution from 1880 to 1920. *Social Science Research 38*(4), 897–920.

Kerr, W. R. and W. F. Lincoln (2010). The supply side of innovation: H-1b visa reforms and us ethnic invention. *Journal of Labor Economics 28*(3), 473–508.

Kim, S. (2007). Immigration, industrial revolution and urban growth in the united states, 1820-1920: Factor endowments, technology and geography. Technical report, National Bureau of Economic Research.

Lafortune, J., J. Tessada, and E. Lewis (2015). People and machines: A look at the evolving relationship between capital and skill in manufacturing 1860-1930 using immigration shocks. Technical report, National Bureau of Economic Research.

Lucas, R. E. (2009). Ideas and growth. *Economica 76*(301), 1–19.

Massey, C. G. (2016). Immigration quotas and immigrant selection. *Explorations in Economic History 60*, 21–40.

Moretti, E. (1999). Social networks and migrations: Italy 1876-1913. *International Migration Review*, 640–657.

Moser, P., A. Voena, and F. Waldinger (2014). German jewish émigrés and us invention. *American Economic Review 104*(10), 3222–55.

Spitzer, Y. and A. Zimran (2014). Migrant self-selection: Anthropometric evidence from the mass migration of italians to the united states, 1907–1925.

Tabellini, M. (2017). Gifts of the immigrants, woes of the natives: Lessons from the age of mass migration.

U.S. Department of Commerce (1924). Statistical Abstract of the United States.

U.S. Department of Commerce (1929). Statistical Abstract of the United States.

U.S. Department of Commerce (1931). Statistical Abstract of the United States.

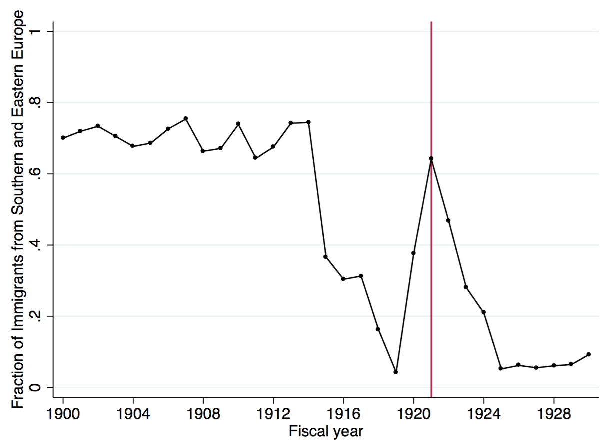
Ward, Z. (2017). Birds of passage: Return migration, self-selection and immigration quotas. *Explorations in Economic History 64*, 37–52.

Willcox, W. F. et al. (1929). International migrations, volume i: Statistics. *NBER Books*.

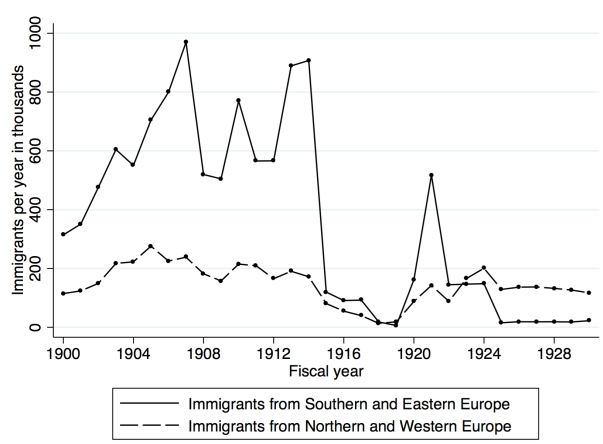
Xie, B. (2017). The effects of immigration quotas on wages, the great black migration, and industrial development.

Figure 1: **Immigration inflows from administrative data**

(a) Total immigration inflows per year

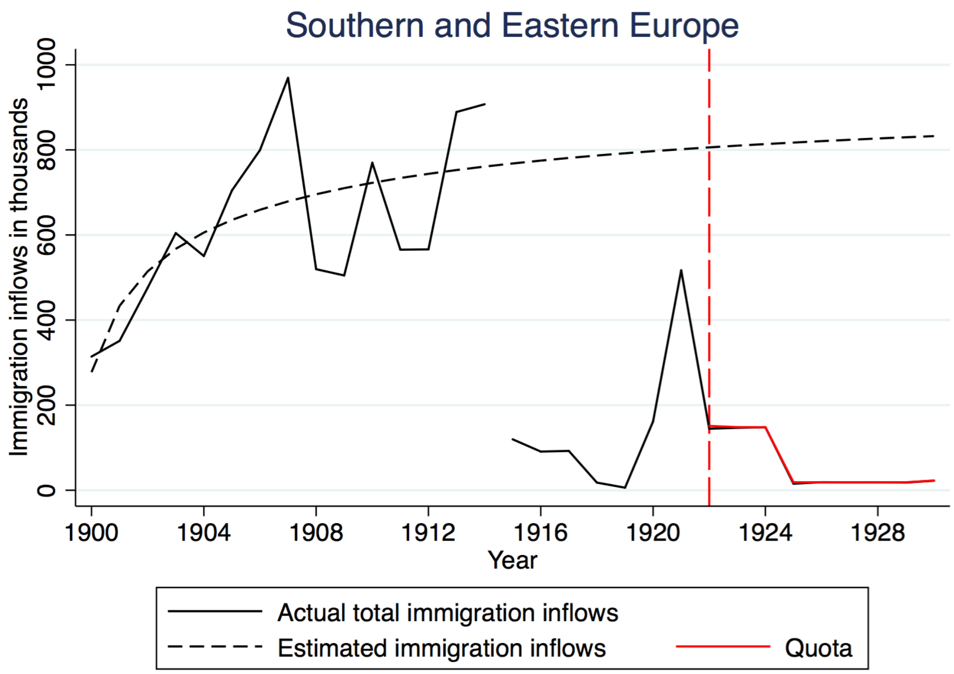


(b) Fraction of immigration from Southern and Eastern Europe

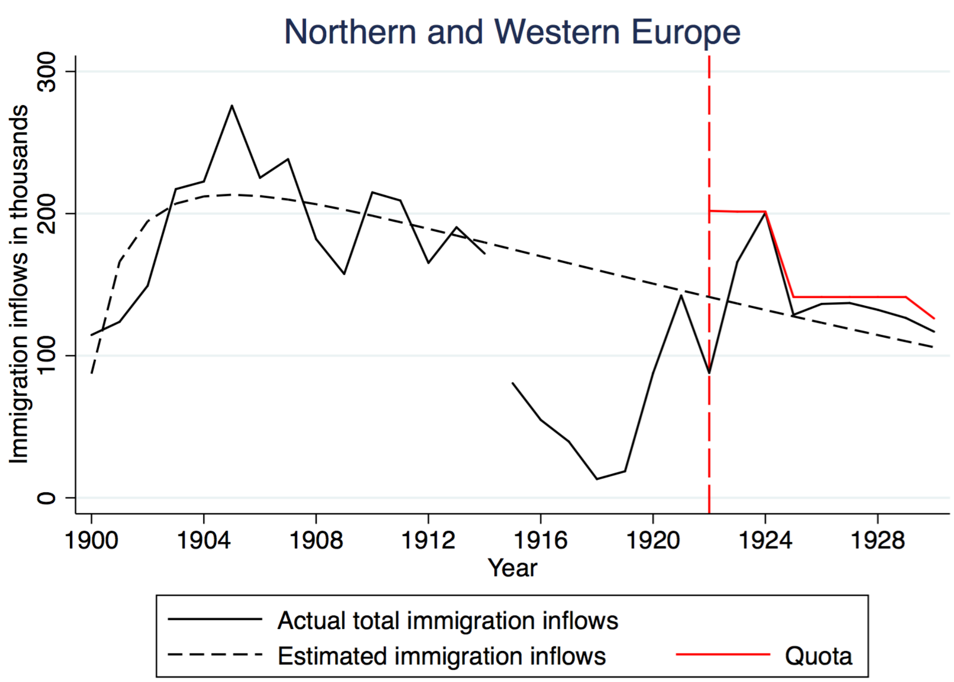


(c) Immigration from Southern and Eastern Europe and Northern and Western Europe

Figure 2: **Immigration inflows under quota by region**



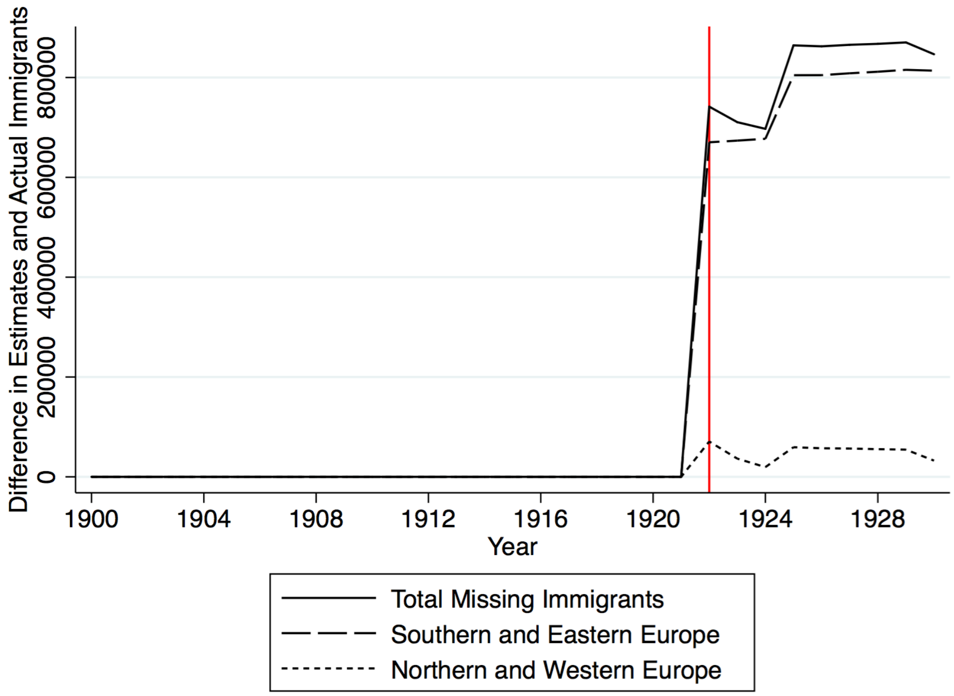
(a) Southern and Eastern Europe



(b) Northern and Western Europe

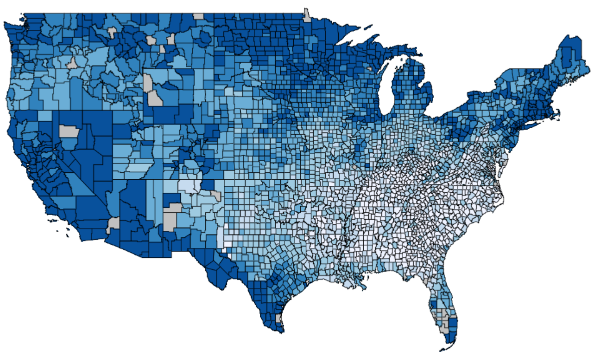
This Figure is a replication of Figure 1 of Ager and Hanson (2018), pg. 31, modified through aggregating immigration into two groups: Southern and Eastern Europe, and Northern and Western Europe. The data from this replication come from Willcox et al.(1929) and U.S. Department of Commerce (1924, 1929, 1931).

Figure 3: **Missing immigration inflows under quota**

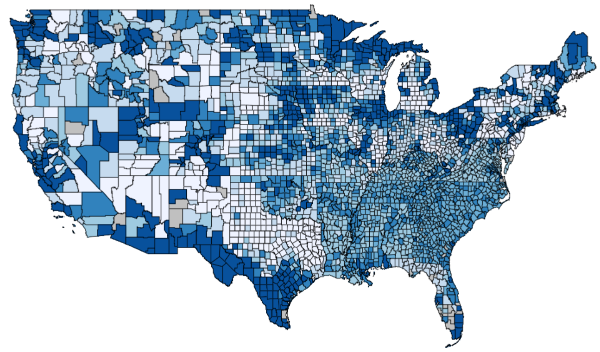


This Figure is a replication of Figure 2 of Ager and Hanson (2018), pg. 31, modified through aggregating immigration into two groups: Southern and Eastern Europe, and Northern and Western Europe. The data from this replication come from Willcox et al.(1929) and U.S. Department of Commerce (1924, 1929, 1931).

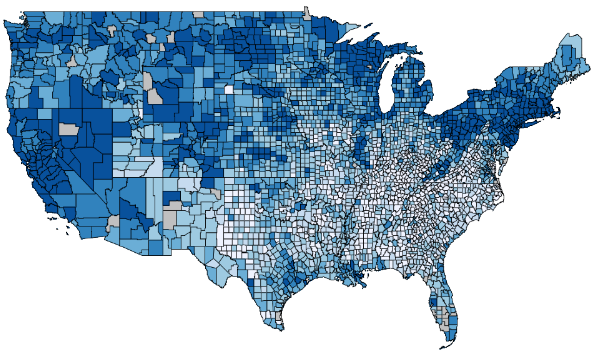
Figure 4: **Geographic distribution of foreign born**



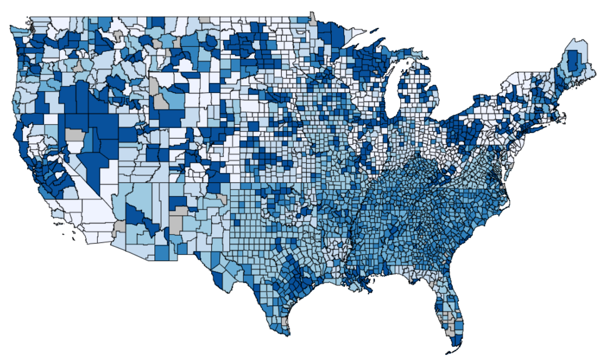
(a) Total foreign born as a fraction of 1920 total population



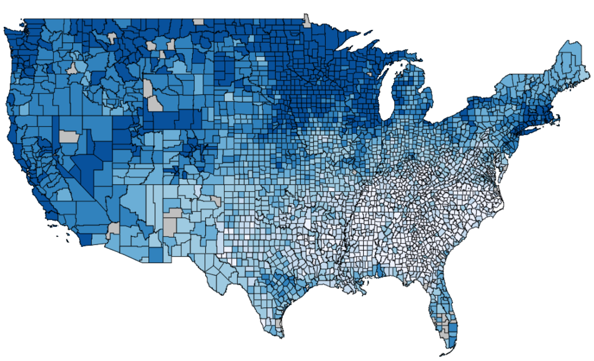
(b) State fixed effects



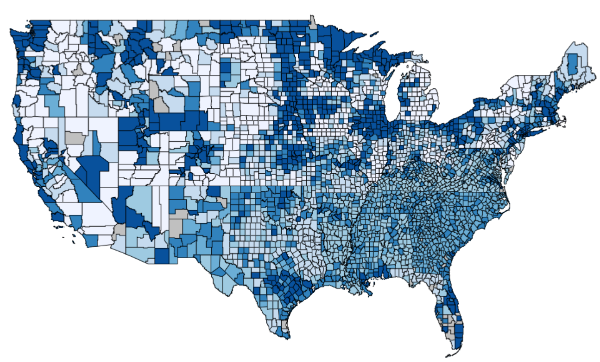
(c) Fraction of foreign born from Southern and Eastern Europe



(d) State fixed effects



(e) Fraction of foreign born from Northern and Western Europe



(f) State fixed effects

Figure 5: **Immigration inflows into quota and non-quota affected cities**

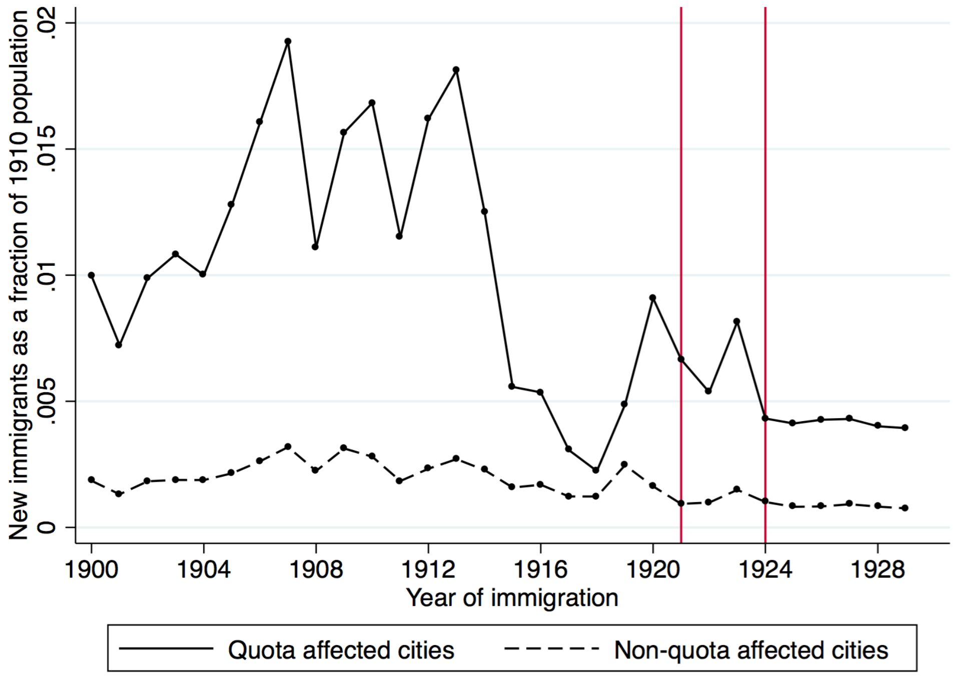
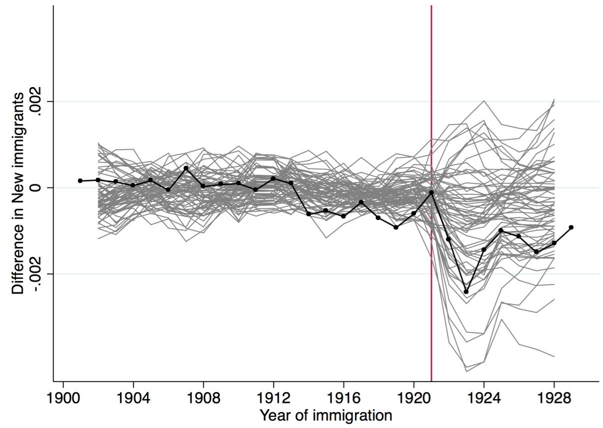
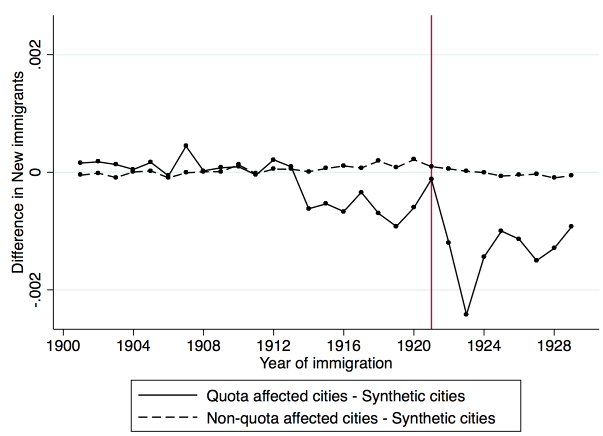


Figure 6: **Synthetic control immigration inflows**



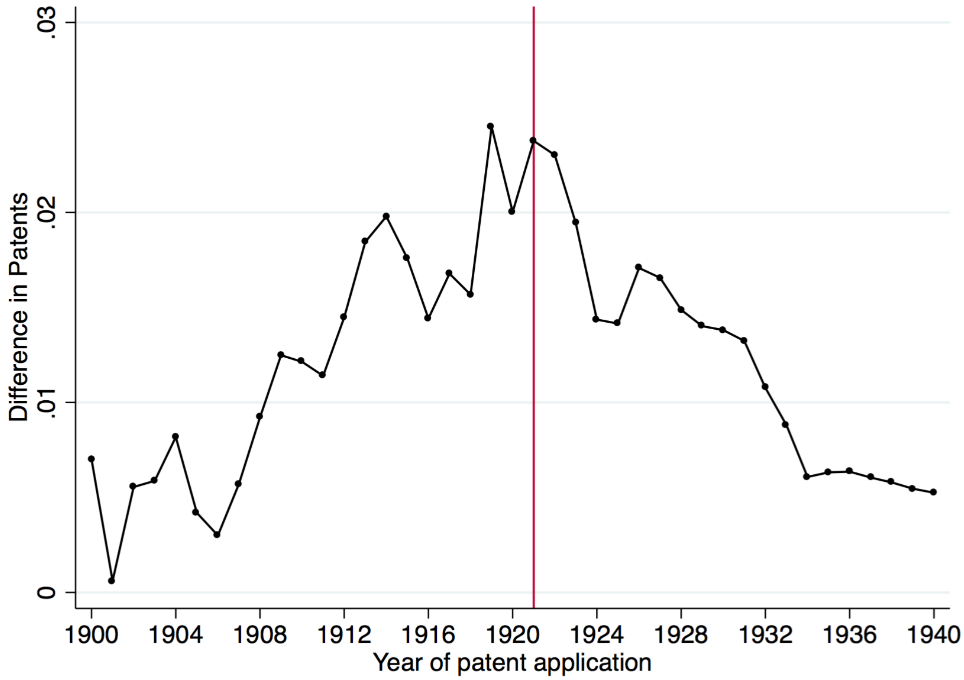
(a) Average difference between treatment and synthetic cities

(b) Average difference between placebo and synthetic cities

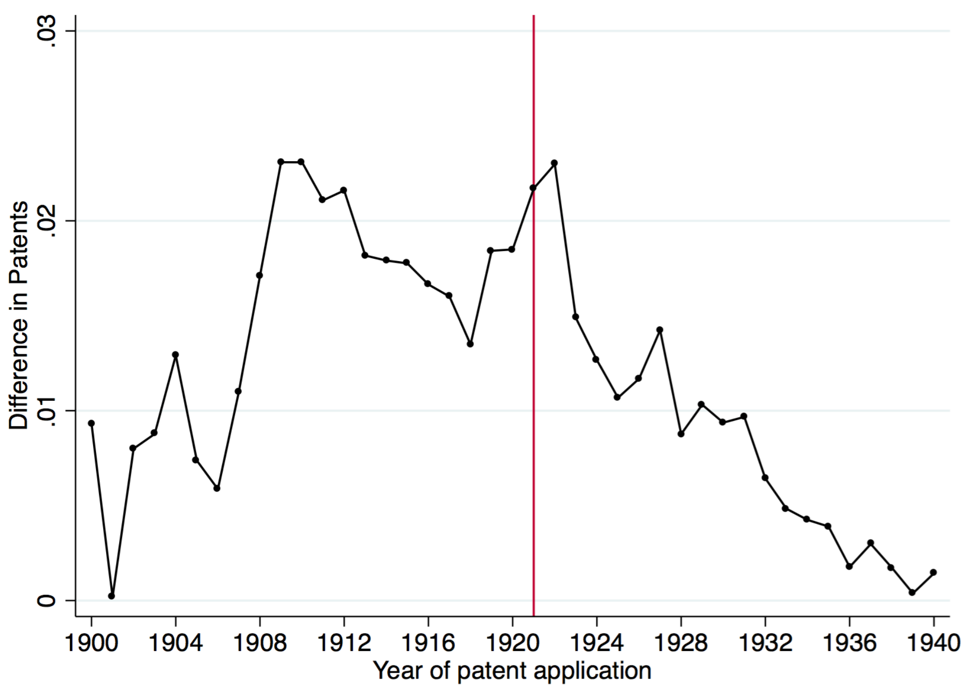


(c) Synthetic control results for treatment and placebo cities

Figure 7: **Patents into quota and non-quota affected cities**

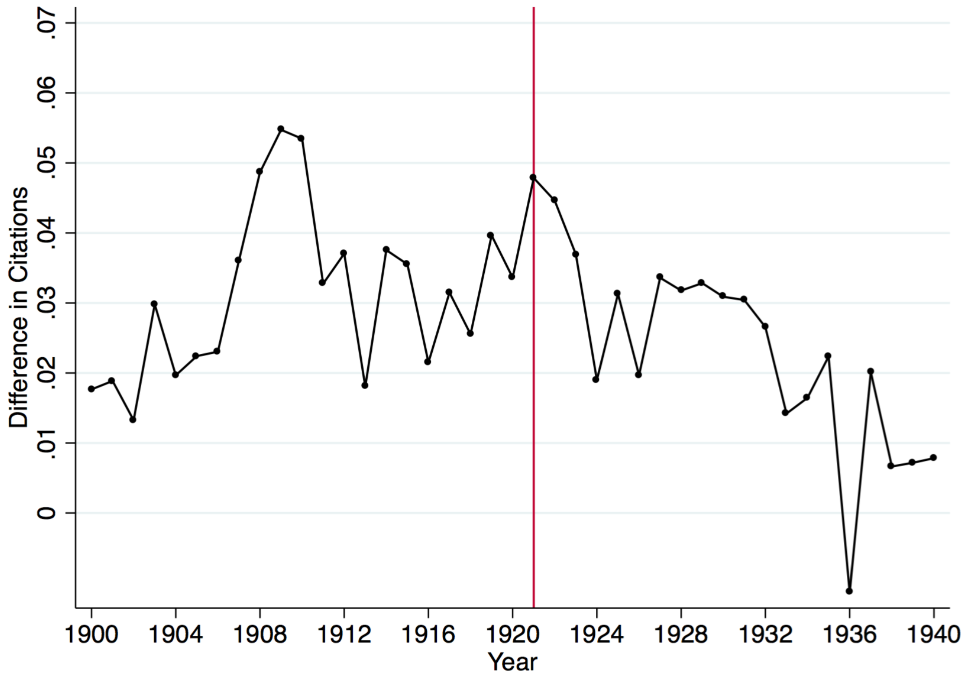


(a) Difference in patents by incumbent inventors in 1919



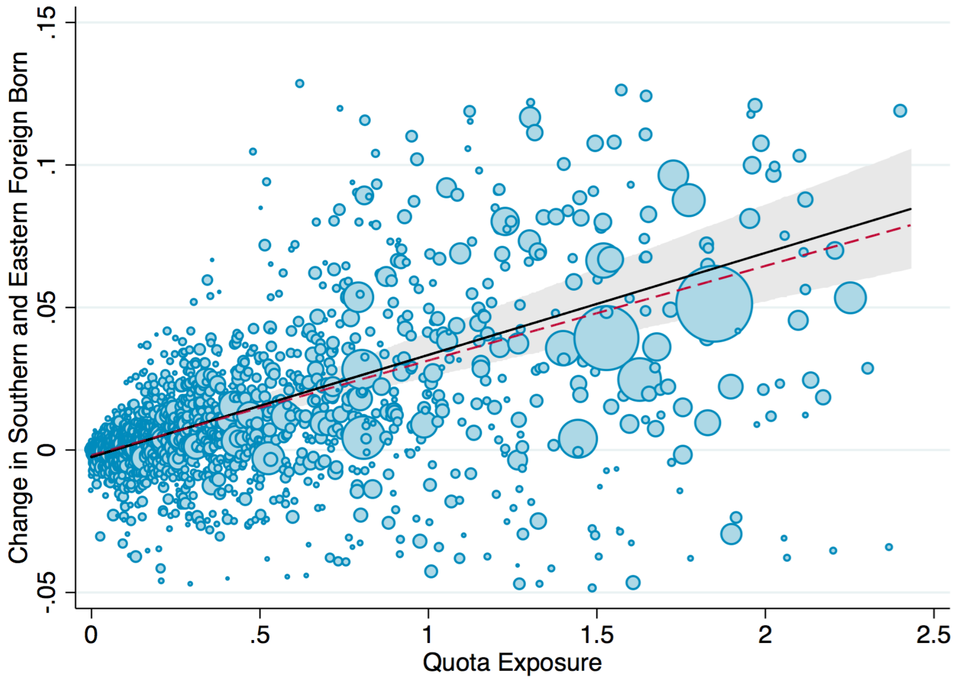
(b) Difference in patents by incumbent inventors in 1910

Figure 8: **Citations into quota and non-quota affected cities**

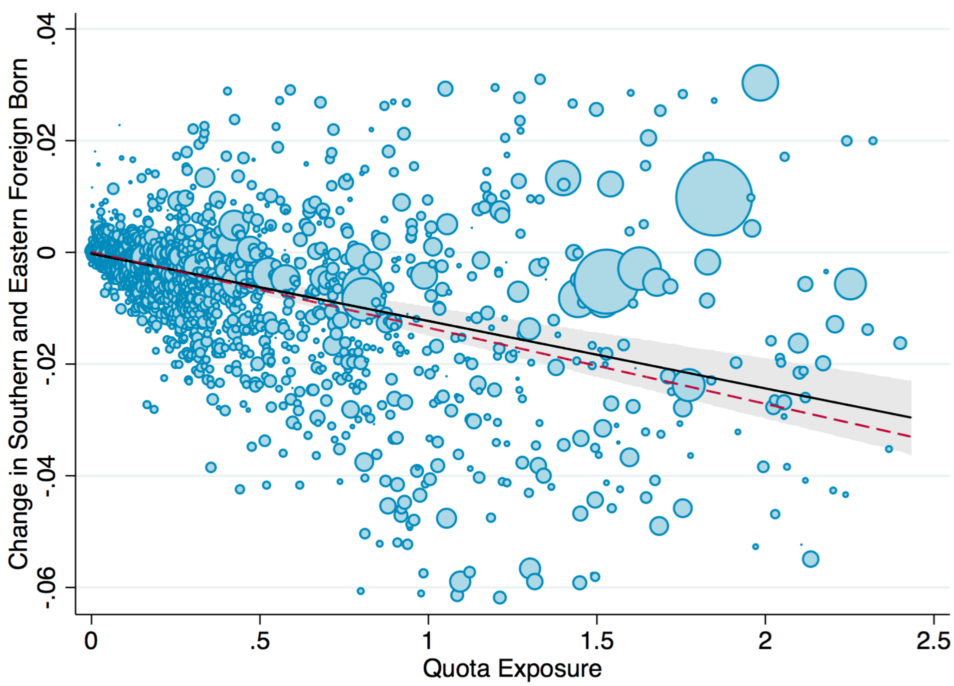


Citations by incumbent inventors in 1910

Figure 9: **Change in foreign born population from Southern and Eastern Europe**

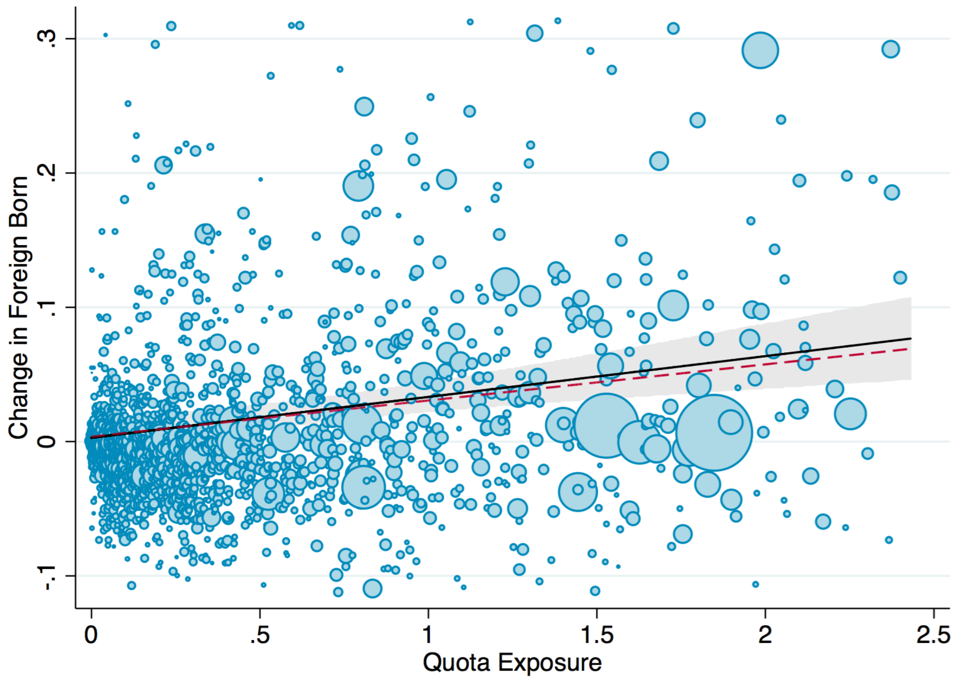


(a) Change between 1910 and 1920 as a fraction of 1910 population

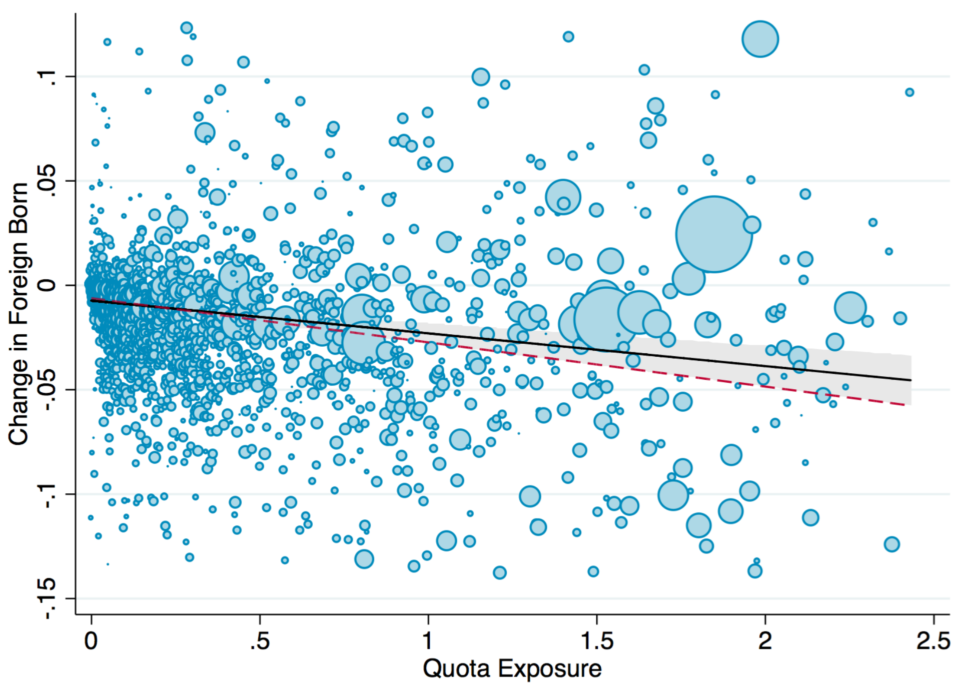


(b) Change between 1920 and 1930 as a fraction of 1920 population

Figure 10: **Change in foreign born population**

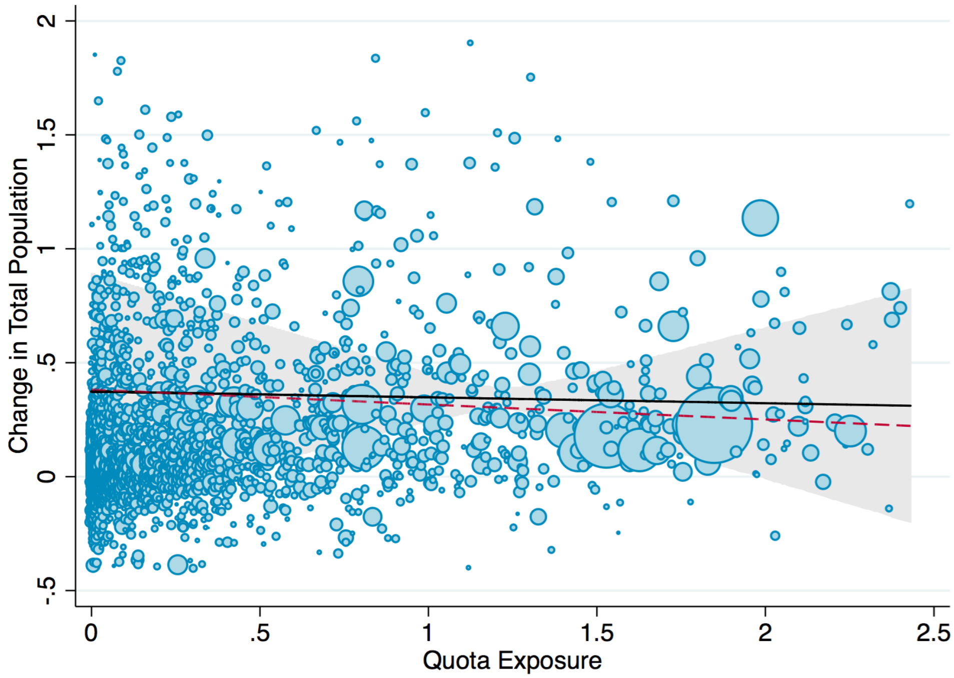


(a) Change between 1910 and 1920 as a fraction of 1910 population

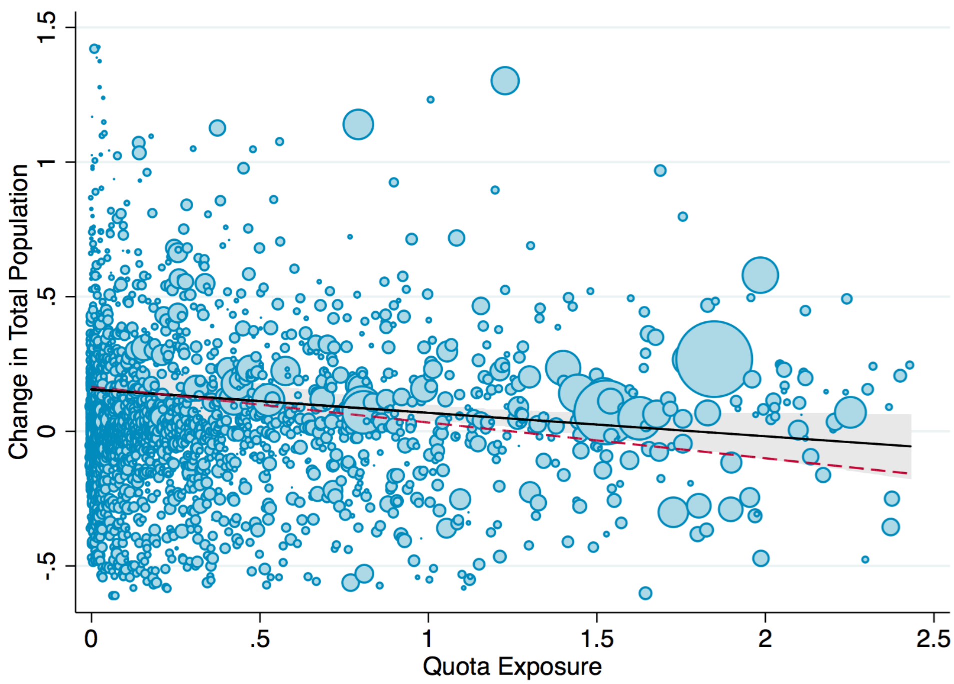


(b) Change between 1920 and 1930 as a fraction of 1920 population

Figure 11: **Change in total population**



(a) Change between 1910 and 1920 as a fraction of 1910 population



(b) Change between 1920 and 1930 as a fraction of 1920 population

Table 1: QUOTA BY COUNTRY

Country	Quota (1)	Actual Immigrants (2)	Missing Immigrants (3)	1920 Population in Thousands (4)	Fraction of Missing Immigrants (5)
A. Southern and Eastern Europe					
Austria	3065	2756	66145	689	0.096
Bulgaria	167	160	7600	10	0.781
Czechoslovakia	6804	6742	3112	319	0.010
Greece	1162	1177	37909	160	0.237
Hungary	2251	2279	67420	407	0.166
Italy	16800	16655	187287	1609	0.116
Poland	13820	13594	129258	1135	0.114
Portugal	1156	1143	12627	113	0.112
Romania	2841	2839	0	92	0.000
Russia	10791	10127	163786	1424	0.115
Spain	405	400	8948	50	0.179
Turkey	714	760	47282	27	1.767
Yugoslavia	2609	2598	31160	128	0.244
Total	62584	61231	762535	6163	0.303
B. Northern and Western Europe					
Belgium	950	931	5918	65	0.091
Denmark	3562	3155	433	186	0.002
Finland	1632	1532	3067	151	0.020
France	4449	4084	4502	155	0.029
Germany	53929	45165	0	1633	0.000
Ireland	27377	21584	0	1051	0.000
Netherlands	2468	2258	6740	133	0.051
Norway	7916	7048	0	367	0.000
Sweden	12361	10758	0	631	0.000
Switzerland	2596	2500	255	121	0.002
UK	42453	37920	20446	1159	0.018
Total	159695	136934	41361	5651	0.019

Notes:
This table shows information on quotas for countries restricted by quota limits. In column 1, 2, and 3, the variable is calculated as the average number per year during the quotas, 1922-1930. Missing immigrants are estimated by the difference between average estimated immigrants per year without quotas based on immigration flows from 1900 and 1914 before the WWI and average actual quota limits per year. Column 5 reports the average missing immigrants as a fraction of 1920 population in that country.

Table 2: SUMMARY STATISTICS

Variables	Treatment Cities	Comparison Cities	Synthetic Cities	Synthetic Weights
Number of Cities	312	2718	1254	1254
A: New Immigrants, Patents and Citations				
New Immigrants per year and city as a Fraction of 1910 Population, 1900-1921	0.0107 (0.0093)	0.0020 (0.0053)	0.0039 (0.0072)	0.0084 (0.0110)
New Immigrants per year and city as a Fraction of 1910 Population, 1922-1929	0.0049 (0.0064)	0.0009 (0.0035)	0.0019 (0.0050)	0.0050 (0.0113)
Patents per year and inventor, 1900-1921	0.1466 (0.1459)	0.1461 (0.2317)	0.1356 (0.1998)	0.1255 (0.1882)
Patents per year and inventor, 1922-1950	0.0427 (0.1005)	0.0468 (0.1731)	0.0379 (0.1326)	0.0359 (0.1286)
Citations per year and inventor, 1900-1921	0.2375 (0.3191)	0.2359 (0.5574)	0.2236 (0.5110)	0.1981 (0.4817)
Citations per year and inventor, 1922-1950	0.1517 (0.3789)	0.1714 (0.6831)	0.1351 (0.4985)	0.1366 (0.6556)
B: Demographic Characteristics				
1910 Population	82439 (244219)	22188 (27766)	24682 (39348)	32697 (65175)
1920 Population	105095 (268008)	25600 (35635)	30219 (50475)	42198 (99980)
1930 Population	112873 (311307)	26238 (45585)	32605 (65361)	60578 (192775)
1910 Foreign Born	25525 (95346)	1786 (4888)	3489 (6792)	7829 (14359)
1920 Foreign Born	27816 (87338)	1829 (5367)	3627 (7498)	8655 (20630)
1930 Foreign Born	26255 (89856)	1521 (6468)	3096 (9274)	10921 (38639)
1910 Southern and Eastern Foreign Born	11694 (52940)	357 (1499)	701 (2151)	1503 (3520)
1920 Southern and Eastern Foreign Born	15474 (53679)	462 (1911)	924 (2739)	2061 (5514)
1930 Southern and Eastern Foreign Born	13941 (52776)	383 (2002)	785 (2894)	2647 (9742)

Notes:
This table shows means and standard deviations in parenthesis. Treatment cities are exposed to quotas in the 90th percentiles, while control cities are not in the 90th percentiles. Synthetic cities exclude control cities with no weight from synthetic matching method. The variables in the last column are weighted from synthetic method. Our main outcome variables of patent and citation come from incumbent inventors who had patents before the year 1910. The number of patents and citations are winsorized at 10 and 20 respectively.

Table 3: EFFECT OF QUOTA ON IMMIGRATION INFLOWS

	Year of Immigration			
	1900-1929		1919-1929	
	Post-Treatment Year			
	1922	1924	1922	1924
	(1)	(2)	(3)	(4)
A. Dependent Variable: New Immigrants as a Fraction of 1910 Population				
Quota Exposure × Post-Treatment	-0.0036***	-0.0037***	-0.0010***	-0.0015***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Dependent Variable Mean	0.0029	0.0028	0.0022	0.0022
Number of Observations	92190	92190	33803	33803
Number of Cities	3073	3073	3073	3073
R-squared	0.5708	0.5691	0.6495	0.6534
B. Dependent Variable: New Immigrants as a Fraction of 1920 Population				
Quota Exposure × Post-Treatment	-0.0028***	-0.0029***	-0.0007***	-0.0010***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Dependent Variable Mean	0.0023	0.0022	0.0016	0.0016
Number of Observations	92190	92190	33803	33803
Number of Cities	3073	3073	3073	3073
R-squared	0.5526	0.5496	0.6740	0.6794

Notes:
The outcome variable of new immigrants is combined from the 1910, 1920, and 1930 Census. Specifically, new immigrants between the years 1900 and 1909 are obtained from the 1910 Census data, and others are extracted in the same fashion. To make a balanced panel data, we restrict data to cities that exist in all censuses.

Table 4: EFFECT OF QUOTA ON POPULATION AND WORKERS

	Southern/Eastern FB		Foreign Born		Total	
	1910-1920 (1)	1920-1930 (2)	1910-1920 (3)	1920-1930 (4)	1910-1920 (5)	1920-1930 (6)
A. Dependent Variable: Change in Population as a Fraction of Total City Population						
Quota Exposure	0.0358***	-0.0121***	0.0304***	-0.0157***	-0.0257	-0.0870*
	(0.0047)	(0.0014)	(0.0081)	(0.0027)	(0.2141)	(0.0450)
Dependent Variable Mean	0.0082	-0.0038	0.0119	-0.0117	0.3660	0.1301
Number of Cities	3208	3327	3208	3327	3208	3327
R-squared	0.1691	0.1230	0.0028	0.0173	0.0000	0.0004
B. Dependent Variable: Change in Workers as a Fraction of Total City Population						
Quota Exposure	0.0092***	-0.0062***	-0.0013	-0.0074***	-0.0188	-0.0292**
	(0.0029)	(0.0008)	(0.0046)	(0.0014)	(0.0551)	(0.0145)
Dependent Variable Mean	0.0010	-0.0018	-0.0030	-0.0043	0.0481	0.0520
Number of Cities	3206	3323	3206	3323	3206	3323
R-squared	0.0561	0.0996	0.0000	0.0151	0.0000	0.0004

Notes:
The dependent variable is the change in the outcome between censuses as a fraction of total population given a city in the previous census. For instance, the change in workers between 1920 and 1930 is the difference in workers between 1920 and 1930 divided by the 1920 population in a city. In Panel B, workers are defined as people aged from 16 to 64 with a specified industry code in the labor force.

Table 5: EFFECT OF QUOTA ON PATENTS

	Year of Patent Application			
	1900-1950		1919-1929	
	Post-Treatment Year			
	1922	1924	1922	1924
	(1)	(2)	(3)	(4)
A. Dependent Variable: Patents by Incumbent Inventors in 1919				
Quota Exposure × Post-Treatment	-0.0018**	-0.0031***	-0.0037***	-0.0046***
	(0.0009)	(0.0009)	(0.0012)	(0.0011)
Dependent Variable Mean	0.1252	0.1206	0.1060	0.0936
Number of Observations	6577575	6577575	1573627	1573627
Number of Inventors	145842	145842	145842	145842
Number of Cities	3311	3311	3311	3311
R-squared	0.2327	0.2327	0.4003	0.4003
B. Dependent Variable: Patents by Incumbent Inventors in 1910				
Quota Exposure × Post-Treatment	-0.0051***	-0.0061***	-0.0039**	-0.0048***
	(0.0017)	(0.0017)	(0.0018)	(0.0015)
Dependent Variable Mean	0.1448	0.1389	0.0808	0.0784
Number of Observations	3700540	3700540	871536	871536
Number of Inventors	81308	81308	81308	81308
Number of Cities	3275	3275	3274	3274
R-squared	0.2655	0.2655	0.4425	0.4425

Notes:
Panel A uses the dependent variable of individual patent data from incumbent inventors who already had at least one patent in 1919 before the quota and pre-treatment periods. In Panel B, the outcome variable is restricted to incumbent inventors who patented before the year 1910. The number of patents is winsorized at 10. Standard errors are clustered by city.

Table 6: EFFECT OF QUOTA ON PATENTS USING SYNTHETIC CONTROL METHOD

	Year of Patent Application			
	1900-1950		1919-1929	
	Post-Treatment Year			
	1922	1924	1922	1924
	(1)	(2)	(3)	(4)
A. Dependent Variable: Patents by Incumbent Inventors in 1919				
Quota Exposure × Post-Treatment	-0.0020**	-0.0034***	-0.0033**	-0.0044***
	(0.0009)	(0.0010)	(0.0014)	(0.0013)
Dependent Variable Mean	0.1252	0.1207	0.1070	0.0945
Number of Observations	5185714	5185714	1237749	1237749
Number of Inventors	114568	114568	114568	114568
Number of Cities	1824	1824	1824	1824
R-squared	0.2243	0.2244	0.3974	0.3974
B. Dependent Variable: Patents by Incumbent Inventors in 1910				
Quota Exposure × Post-Treatment	-0.0058***	-0.0068***	-0.0034*	-0.0046***
	(0.0019)	(0.0020)	(0.0021)	(0.0016)
Dependent Variable Mean	0.1443	0.1384	0.0810	0.0785
Number of Observations	2906830	2906830	682911	682911
Number of Inventors	63621	63621	63621	63621
Number of Cities	1802	1802	1801	1801
R-squared	0.2584	0.2584	0.4459	0.4460

Notes:
The table reports the estimated coefficients using inventors in quota affected cities and all the cities with positive weights in control group from the synthetic control method. Cities with no weight are excluded in the regression. Panel A uses the dependent variable of individual patent data from incumbent inventors who already had at least one patent in 1919 before the quota and pre-treatment periods. In Panel B, the outcome variable is restricted to incumbent inventors who patented before the year 1910. The number of patents is winsorized at 10. Standard errors are clustered by city.

Table 7: EFFECT OF QUOTA ON CITATIONS

	Year			
	1900-1950		1919-1929	
	Post-Treatment Year			
	1922	1924	1922	1924
	(1)	(2)	(3)	(4)
A. Dependent Variable: Citations by Incumbent Inventors in 1919				
Quota Exposure × Post-Treatment	-0.0036	-0.0060**	-0.0088**	-0.0090**
	(0.0023)	(0.0024)	(0.0041)	(0.0037)
Dependent Variable Mean	0.2222	0.2186	0.2404	0.2175
Number of Observations	6577575	6577575	1573627	1573627
Number of Inventors	145842	145842	145842	145842
Number of Cities	3311	3311	3311	3311
R-squared	0.1442	0.1442	0.2264	0.2264
B. Dependent Variable: Citations by Incumbent Inventors in 1910				
Quota Exposure × Post-Treatment	-0.0109***	-0.0130***	-0.0077	-0.0103**
	(0.0033)	(0.0034)	(0.0069)	(0.0049)
Dependent Variable Mean	0.2402	0.2353	0.1828	0.1825
Number of Observations	3700540	3700540	871536	871536
Number of Inventors	81308	81308	81308	81308
Number of Cities	3275	3275	3274	3274
R-squared	0.1616	0.1616	0.2536	0.2536

Notes:
Panel A uses the dependent variable of individual citation data from incumbent inventors who already had at least one patent in 1919 before the quota and pre-treatment periods. In Panel B, the outcome variable is restricted to incumbent inventors who patented before the year 1910. The number of citations is winsorized at 20. Standard errors are clustered by city.

Table 8: EFFECT OF QUOTA ON INDUSTRY WORKFORCE

	Year of Immigration			
	1900-1929		1919-1929	
	Post-Treatment Year			
	1922	1924	1922	1924
	(1)	(2)	(3)	(4)
Dependent Variable: Industry Immigration Inflows as a Fraction of Total Workers				
Quota Exposure × Post-Treatment	-0.0944*	-0.0777**	-0.0593	-0.0307***
	(0.0524)	(0.0378)	(0.0359)	(0.0112)
Dependent Variable Mean	0.0157	0.0190	0.0207	0.0280
Number of Observations	2920	2920	1606	1606
Number of Industries	146	146	146	146
R-squared	0.4073	0.4056	0.7682	0.7677

Notes:
The dependent variable of industry workforce is the number of new immigrants per year divided by total native workers in 1920 in that industry.

Table 9: EFFECT OF QUOTA ON INDUSTRY-AFFECTED PATENTS

	Incumbent Inventors Before the Year			
	1919		1910	
	Post-Treatment Year			
	1922	1924	1922	1924
	(1)	(2)	(3)	(4)
A. Dependent Variable: Patents Related to Affected Industry				
Quota Exposure × Post-Treatment	-0.0034***	-0.0041***	-0.0045***	-0.0048***
	(0.0012)	(0.0012)	(0.0017)	(0.0015)
Dependent Variable Mean	0.0965	0.0853	0.0748	0.0727
Number of Observations	1572390	1572390	870996	870996
Number of Inventors	145842	145842	81308	81308
Number of Cities	3311	3311	3274	3274
R-squared	0.4271	0.4271	0.4974	0.4974
B. Dependent Variable: Patents Unrelated to Affected Industry				
Quota Exposure × Post-Treatment	-0.0004	-0.0005	0.0004	0.0001
	(0.0003)	(0.0003)	(0.0004)	(0.0004)
Dependent Variable Mean	0.0078	0.0071	0.0056	0.0054
Number of Observations	1572390	1572390	870996	870996
Number of Inventors	145842	145842	81308	81308
Number of Cities	3311	3311	3274	3274
R-squared	0.2853	0.2853	0.2750	0.2750
C. Dependent Variable: Patents Unrelated to Moderately Affected Industry				
Quota Exposure × Post-Treatment	-0.0003	-0.0004	0.0004	0.0002
	(0.0003)	(0.0003)	(0.0003)	(0.0004)
Dependent Variable Mean	0.0060	0.0054	0.0041	0.0040
Number of Observations	1572390	1572390	870996	870996
Number of Inventors	145842	145842	81308	81308
Number of Cities	3311	3311	3274	3274
R-squared	0.3046	0.3046	0.2929	0.2929

Notes:
The outcome variable of patents related to affected industry is calculated by adding up patents related to 75th percentile of treatment industry. Affected industry and moderately affected industry have the industry treatment variable in 75th percentiles and 50th percentiles respectively. The year of patent application covers from 1919 to 1929.