Labor and Invention as Complements: Evidence from 1920s Immigration Quotas

Colin Davison Kirk Doran Chungeun Yoon

University of Notre Dame

October, 2024

Abstract

Economists have long posited that scarce labor should encourage invention (Hicks 1932). We provide the first causal evidence of mass low skilled immigration's effect on invention, using variation induced by 1920s quotas to the United States, which ended history's largest international migration. Both counties and individual inventors exposed to fewer low-skilled immigrants applied for fewer patents. Firms with large establishment sizes disproportionately decreased their invention, suggesting invention depends on the scale of labor in production. In early twentieth century America, the increasing scarcity of labor discouraged invention, in part because labor scale and invention were complements.

JEL: J24, N32, O31

Keywords: Immigration, Invention, Economies of Scale

We thank Pierre Azoulay, George Borjas, Brian Cadena, Prithwiraj Choudhury, Bill Evans, Ina Ganguli, Britta Glennon, Walker Hanlon, Exequiel Hernandez, Daniel Hungerman, Ben Jones, Joseph Kaboski, Shu Kahn, Bill Kerr, Adriana Kugler, Ethan Lieber, Francesco Lissoni, Megan MacGarvie, Petra Moser, Gabriele Pellegrino, Sergio Petralia, Marco Tabellini, Reinhilde Veugelers, Fabian Waldinger, Bruce Weinberg, Heidi Williams, Abigail Wozniak, and seminar participants at the NBER 2019 Summer Institute and GEOINNO2018. We thank Grace Enright and Cody Kankel for excellent research assistance. All errors are our own.

I Introduction

How does mass immigration affect invention? Most of the research on the relationship between immigration and invention has focused on the effect of selective highly skilled migration on innovation (Kerr, Kerr, et al. 2016; Hunt and Gauthier-Loiselle 2010; Bernstein et al. 2022b). Mass low skilled migration's effect on innovation has received less attention and has provided mixed evidence (Bratti and Conti 2018; Pinate et al. 2023). This lack of literature is especially surprising, because some of the largest changes in the labor force arise from mass low skilled immigration, with a recent example being the successive waves of low skilled immigrants and refugees that have entered Europe and the United States over the past fifteen years (Edo and Özgüzel 2023).

In this paper, we focus on a particular historical episode to bring clarity to this question: the closing of the United States' borders in the early 20th century. The 1921 Emergency Quota Act and the 1924 Immigration Act together combined to reduce immigration from Southern and Eastern Europe to the United States by about ninety percent, with plausibly no effect on migration from the rest of Europe (Abramitzky et al. 2023). Because new immigrants chose locations within the United States based on where compatriots had already settled, and because the decreased immigration flows were mostly low skilled, this episode constitutes an ideal experiment for determining the effect of decreases in mass low skilled migration on localized invention.

We construct a panel dataset on patenting at the individual inventor and county levels using the PATSTAT Database, the PatentCity Database, and the United States Censuses from 1900 to 1930. Focusing on variation due to the 1921 and 1924 Quotas, we use a measure of local quota exposure developed by (Abramitzky et al. 2023) to determine which inventors and counties were exposed to greater declines in immigrants after the Quotas. We find that both inventors and counties exposed to fewer immigrants sharply reverse their trends in patenting, with a decrease of eleven percent among inventors and fifteen percent at the county level relative to the mean.

Mass immigration has many channels through which it can affect invention, but one of the potentially important ones is a change in the scale of the local labor force, which could affect the possibilities for division of labor and the machinery, products, and processes that are complementary with it (**atack2015division**). Using variation in establishment sizes across firms from the 1929 Census of Manufactures, we find that firms which depended on larger establishment sizes saw larger declines in invention when exposed to a quota-related decline in local immigration. This suggests that one important channel behind our results is the scale of the labor force; in early twentieth century American firms, labor and invention were often complements.

It is worthwhile to briefly develop an initial intuition for these results. Intuitively, it would seem that mass immigration should discourage inventions which economize on labor, not encourage them. Indeed, since (Hicks 1932), economists have posited that plentiful factors of production will discourage inventions that economize on the plentiful factor. The famous Habakkuk hypothesis (Habakkuk 1962) applied this argument to the first Industrial Revolution, positing that relatively scarce labor in early nineteenth century America incentivized invention. But these classic and intuitive arguments are incomplete.[1]

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 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 full advantage of the division of labor, the new assembly line required 14,000 local employees.[2] Thus, it is possible that the inventions characteristic of America's second industrial revolution were only worthwhile to be produced in the context of plentiful local labor supply. The era of mass migration may have provided necessary fuel for the era of great American invention.[3]

In the rest of the paper, we provide historical context, review the literature, describe the data, discuss the empirical strategy, and explain the results. In our conclusion, we consider implications for future research.

[1]For example, the theoretical results in (Acemoglu 2010) show that, contrary to Hicks and Habakkuk, plentiful labor supply will encourage invention whenever new technology increases the marginal product of labor, and that indeed this is how technology is conceptualized in all canonical macroeconomic models.

[2]Furthermore, the work was so repetitive (and thus turnover so rampant), that the actual number of employees required in a year was considerably higher than 14,000 (III 1981)

[3]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 **hirschman2009immigration** been complementary with assembly-line machinery **lafortune2018people** and allowed for larger, more productive firms **kim2007immigration**

II History and Literature Review

II.I Historical Context

Between 1850 and 1920, over 30 million Europeans migrated to the United States (Abramitzky et al. 2023). 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. Southern and Eastern Europeans comprised an increasing portion of the immigrants as the century progressed. While the effects of low-skilled immigration were hotly debated, Abramitzky et al. 2023 point out that there were economists at the time who believed low-skill migrants were complementary to higher-skilled native workers.

American concerns about the effects of immigration grew in proportion to the increased prevalence of Southern and Eastern European immigrants (Tabellini 2020). 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.

II.II Literature Review

There is a small but growing empirical literature on the effects of low-skilled immigration on firms. A recent example is (Clemens and Lewis 2022), which exploits lotteries for H-2B immigrants to the United States to determine that firms which obtain random low-skilled immigrants increase their investment and output, without typically affecting employment of domestic workers. On the other hand, (Muñoz 2024) finds that European firms which receive migrant workers employ fewer domestic workers as a result, without affecting domestic wages. This literature is still in its infancy, but the results already suggest that low-skilled immigrants do not leave receiving firms unchanged, and can affect both production and investment, with varied effects on the labor market for domestic workers.

There is another small literature that relates low-skilled immigration to invention at the regional level. Bratti and Conti 2018 found no evidence of either positive or negative effects of low-skilled migrants on innovation, while Pinate et al. 2023 documented a negative association between low-skilled migrants and patents and a positive association for high-skilled migrants. Our study contributes to this literature by finding that the reduction in low-skilled migrants had a strong, negative effect on innovation in the context of the US immigration quotas of the 1920s, and this effect arose through the mechanism of decreased labor scale of establishment size in production.

Both low skilled and high skilled immigration affect the scale of the labor force, and could therefore indirectly affect invention through effects on establishment size, demand for goods, and product diversity. Only high skilled immigration directly affects invention, such as the case when immigrants invent themselves or bring knowledge spillovers to native inventors. At the broadest level, (Bernstein et al. 2022a) finds that highly-skilled immigrants to the United States account for a disproportionate share of patent output directly, and an even more disproportionate share indirectly through spillovers to native inventors. A large set of papers including (Doran et al. 2022) and (Kerr and Lincoln 2010) study the effect of specific policy shocks to high-skill immigration rates and find varied effects of high-skilled immigration on patenting, depending on the unit of observation, the identification strategy, and the policy context.

There is a growing empirical literature on the effects of the 1920s immigration quotas. This paper is an update of a previous draft (Yoon and Doran 2020), which was an early paper in that literature; this new paper subsumes that earlier draft. Papers in this literature include (Abramitzky et al. 2023), (Tabellini 2020), (Moser and San 2020), and (Morrison and Costas n.d.). Both (Abramitzky et al. 2023) and (Tabellini 2020) exploit the quotas to study native employment effects of immigration, finding either null or positive effects, respectively. Both (Moser and San 2020) and (Morrison and Costas n.d.) exploit the quotas to study innovation effects of immigration, but they differ from and complement this paper. Moser and San 2020 study the effects of the 1920s quotas on the productivity of US scientists. Their study is in the spirit of the literature on the effects of high skilled immigration on innovation, looking at how missing scientists, due to the quotas, affect US scientists. As such, Moser and San 2020 use variation in quota exposure at the field level which captures the missing scientists from the quotas, similar to Borjas and Doran 2012. In contrast, our study examines how the reduction of low-skilled migrants due to the quotas impacts innovation. To operationalize this, we use variation in quota exposure at the geographic level, similar to the labor market shocks examined by Abramitzky et al. 2023. Morrison and Costas n.d.) uses the geographic variation in quota exposure as well, updating the outcome variables in (Yoon and Doran 2020) to study breakthrough innovations among patents.

Finally, we can also situate our findings in the theoretical literature relating labor, innovation, and technological change. We will show below that scarce labor leads to fewer patented innovations by firms with large establishment sizes. This finding is consonant with the existing literature in two ways. First, we note that purely labor-augmenting technological change in the aggregate may arise due to innovations that are embodied in capital, as (Jones and Liu 2024) demonstrate. Second, technological change that is capital augmenting, in a world in which labor and capital are complements, will tend to decrease whenever labor becomes more scarce, as (Acemoglu 2010) demonstrates. Thus, our finding that scarce labor leads to fewer patented innovations by firms with large establishment sizes is consistent with a broad literature showing that the elasticity of substitution between capital and labor is less than one (see (Hamermesh 1993), (Chirinko 2008), (Antràs 2004), (Oberfield and Raval 2021), as well as a world in which large establishments in particular make heavy use of technology embodied in capital.

III Data

III.I Population Characteristics

To measure characteristics about the population we use the 1900, 1910, 1920, and 1930 Full Count Censuses[4]. These data provide information on each individual's sex, country of birth, year of immigration, age, and occupation. We use this information to construct various population characteristics at the county[5] level. We also use the aggregated 1920 U.S. Census data at the county level provided by Haines 2010 to calculate the share of the population living in urban areas, the share of land being used as farmland, the share workers

[4] We do not use the 1940 Full Count Census as it does not provide information on the year of immigration.
[5] We use a balanced panel of 2,804 counties that appear in all decennial censuses between 1900-1930.

employed in manufacturing, and manufacturing value added per manufacturing employee in the county. These variables serve as control variables in our specifications.

III.II Quota Exposure

We follow Abramitzky et al. 2023 and measure the exposure a county, c, has to the quotas in Equation (1). FB_{ac1920} is a count of the number of foreign born residents living in county c who came from area of the world[6], a. This count of foreign born residents from an area of the world is then multiplied by the quota intensity for that area of the world. Quota intensities are calculated as the difference between the predicted number of immigrants from that area of the world, absent the quota policy, and the number of quota slots from that area of the world, with the difference being normalized by the predicted number of immigrants from that area of the world, absent the quota policy.[7] These are then summed across all areas of the world and normalized by the 1920 population in the county. In our specifications we use a binary treatment indicator where we consider counties which are above the 50th percentile in the quota exposure metric to be highly exposed to quotas and thus treated, and counties below the 50th percentile in the quota exposure metric to be untreated.

$$\text{QE}_c = \frac{\sum_a FB_{ac1920} \times \text{Quota Intensity}_a}{Pop_{c1920}} \tag{1}$$

III.III Innovation

III.III.1 County Level

To measure innovation we use patent data, as it provides a way of identifying the geography of the innovation and the firms and inventors associated with an innovation. We utilize the PatentCity database provided by Bergeaud and Verluise 2024 which provides the latitude and longitude of each inventor $\times$ patent observation based on the written location of the inventor provided in patent documentation. We then match inventor $\times$ patent observations to US counties based on the provided latitudes and longitudes. When aggregating patenting activity to the county $\times$ year level, each county $\times$ year observation receives one patent for each patent application having at least one inventor residing in the county. We measure innovative activity at the county level using the number of ultimately granted patents applied for in a year, scaled by thousand male working age individuals residing in the county in 1920.

[6] Abramitzky et al. 2023 use area of the world instead of country of origin. For example, Abramitzky et al. 2023 aggregate all countries in Central Europe together into one area.

[7] See Abramitzky et al. 2023 for more detail on how predicted number of immigrants, absent the quota policy, is calculated.

III.III.2 Inventor Level

To measure innovation at the inventor level, we require the disambiguation of inventors in the patent data which is not provided by the Bergeaud and Verluise 2024 data. We start by merging the patent record in PATSTAT[8] with the 1920 Full Count Census by conducting a fuzzy match between the provided inventor name in PATSTAT and the name record in the 1920 Full Count Census. To increase the probability of accurate matching, we restrict the 1920 Full Count Census to individuals who have a unique name[9]. Further, we only consider matching patent applications when the inventor's implied age at the time of the application is between 18 and 80. For each inventor who matches to a uniquely named individual in the 1920 Census, we create a panel dataset of the number of ultimately granted patents the inventor applies for in each year between 1900-1940. In order to have a balanced panel of inventors and to examine the effect of quotas on pre-existing inventors, we restrict to incumbent inventors who had patented at least once before 1921.

Our matched dataset is likely to result in little error. Since all inventors must patent before 1921, then anyone born after 1902 could not be in our dataset as they would have no opportunity to patent before 1921 as they must be at least 18 years old to patent in our data. Individuals born between 1901-1902 would be 18 years old by 1919 at the earliest. As the 1920 Census was enumerated in 1919, these individuals could not be confused for another person who was uniquely named in the 1920 Census. It is possible that someone born in 1900 with the same name as a uniquely named individual in the 1920 Census patented in 1918 when they turned 18 and then subsequently died before the enumeration of the 1920 Census in 1919. Even if we assumed that all individuals born in 1900 and patenting in 1918 were confused with a uniquely named individual in the 1920 Census, this would only misattribute 0.05% of the patents in our data.

III.III.3 Firms

To identify firms, we start with establishment-level data created from the 1929 Census of Manufacturers (CoM) and provided by Vickers and Ziebarth 2023.[10] The Vickers and Ziebarth 2023 data provide information on establishments belonging to 25 industries that comprise approximately 20% of 1929 manufacturing output. Since we are interested in the innovative activity of firms, we limit our sample to "high-tech" industries, which include: petroleum refining, glass, blast furnaces/steel works, agricultural implements, aircraft, motor

[8] PATSTAT provides patenting data from 1898-present.

[9] 43% of individuals in the 1920 Full Count Census have a unique name

[10] While CoMs were enumerated from 1880-1929, these CoMs have been lost due to "fire, bureaucratic neglect, or active destruction to conserve space at the National Archives." (Vickers and Ziebarth 2020).

vehicles, and radio equipment. This leaves us with 2,022 establishments.

With this establishment-level data, we next group establishments into firms. To do this, we start by cleaning the raw text for the name of the establishment, the name of the owner, and the name of the parent firm using a firm name cleaner provided by Arora et al. 2020.[11] For each establishment, we assign it a firm name by prioritizing the name of the owner if it is not missing. In cases where the owner is missing, we use the parent firm name, and finally in cases where both the owner and parent firm are missing we use the establishment name. We then manually harmonize the names of establishments so that all establishments belonging to the same firm share the firm's name. For example, the establishment with the establishment name: "FORD MOTOR CO HOUSTON TEXAS BRANCH" was originally given the firm name "MR HENRY FORD" as "MR HENRY FORD" was listed as the owner of the establishment. We manually correct this so that the establishment is given its harmonized and proper firm name: "FORD MOTOR".

To prepare the PATSTAT data for matching with the CoM data, we start by limiting to all patents filed for by firms[12] and then we clean the firm names[13] using the firm name cleaner provided by Arora et al. 2020. For each firm name in the establishment data, we then match the firm to the patent record through a fuzzy matching procedure based on firm name which is detailed in Appendix A. Although, error in matching cannot be completely eliminated, visual inspection of the matches confirms that these criteria limit the number of incorrect matches while identifying most of the correct matches. We next remove firms who we identify as having filed for zero patents in the pre-quota time period between 1900-1921. In the end, we create a balanced panel of 373 incumbent firms' patenting activity from 1900-1940.

To identify the quota exposure faced by firm, we start by identifying the county of each establishment and matching it with its county level quota exposure metric calculated in Section III.II. We then aggregate quota exposure up to the firm level by taking the weighted mean quota exposure across a firm's establishments where the weights are the number of wage earning employees employed at the establishment.

[11]Only one establishment has a missing name for the establishment, 19% of establishments have a missing owner name, and 83% of establishments have a missing parent firm name.

[12]In PATSTAT, this is achieved by filtering to patents where psn_sector is equal to "COMPANY".

[13]In PATSTAT, firm names are identified using the psn_name field.

IV Empirical Strategy and Results

IV.I Population Characteristics

We first examine the effect that the quotas had on the workforce of counties. To do this, we estimate the following first differences regression specification where the dependent variable is the first difference in outcome Y_{crt} for county c, belonging to region r, across time period τ. $\mathbb{1}\{\mathrm{QE}_c\}$ is an indicator for whether the county is above the 50th percentile in the quota exposure metric. Taking first differences of the outcome variable removes level differences in outcomes and region by year fixed effects control for differential time trends in first differences across regions. $\mathbb{1}\{\mathrm{Post}_\tau\}$ is an indicator that is one for the 1920-1930 first difference and zero otherwise. Standard errors are clustered at the county level. β_2 is the coefficient of interest and captures the change in trend for a given outcome variable in treated counties relative to control counties after the institution of the quota policy.

$$\Delta \mathrm{Y}_{cr\tau} = \beta_1 \mathbb{1}\{\mathrm{QE}_c\} + \beta_2 \left(\mathbb{1}\{\mathrm{QE}_c\} \times \mathbb{1}\{\mathrm{Post}_\tau\}\right) + \phi_{r\tau} + \varepsilon_{cr\tau} \tag{2}$$

We estimate Equation (2) with three outcome variables that capture different dimensions of how the quota policy affected the workforce. First, we confirm that higher quota exposure had a large negative effect on the share of a county's workforce who is newly immigrated from a quota exposed area of the world. Second, we examine how quotas affected the share of a county's workforce that is foreign born. Finally, we investigate how quota exposure altered the low skill share of the workforce.

Table 1 presents the results. In column (1), the dependent variable is the change in the share of the population who are newly immigrated working age men from a quota exposed country [14]. Column (1) shows that the quotas had a large negative effect on the arrival of new immigrants from quota exposed countries. While the mean share of the population who are newly arrived working age men from quota exposed countries is quite small, the effect off the mean is quite large. Counties that had a high exposure to quote policies saw a 95% decline in new immigrants from quota exposed countries off of mean levels. In Column (2), we add controls variables interacted with a post dummy, to control for the fact that the urban share, manufacturing share, or productivity of manufacturing before the quotas were implemented may lead counties to experience differential trends in population characteristics after the quotas were implemented. While the point estimate declines some in column (2), the estimate is still large and highly significant, indicating a 68% decline

[14] The working age is 16-65. New immigrants are those who have immigrated within the last 10 years of the current Census year. Countries exposed to quotas are the those countries with near complete restrictions on the number of immigrants (Southern/Eastern European countries) as defined by Abramitzky et al. 2023.

in new immigrants from quota exposed countries. Column (3) shows that quota exposure led to a 17% reduction in the share of the population that is male working age and foreign born, off a mean level of 3.5%, with the result being robust to the inclusion of controls in column (4). As expected, columns (1)-(4) show that the quota policy led to a reduction in the number of immigrants and lowered the share of the population that was foreign born. Column (5) examines whether this reduction in immigrant labor had an effect on the skill composition of the labor force. Given that immigrants from quota exposed countries were disproportionately of lower skill, we would expect the low-skill labor share to fall in response to quota exposure. To measure the skill level of a county, we use a measure from the Census[15] that indicates the share of people in a person's occupation who have completed at least some college and then subtract one to arrive at the low-skill share of workers. Column (5) shows that high quota exposure led to a 0.7 percentage point reduction in a county's low-skill share after the introduction of the quota policies, consistent with migrants from quota exposed countries being disproportionately of lower skill; the result is similar with the inclusion of controls. Table B.1 shows that the results are robust to the inclusion of county fixed effects which control for the average changes in the population characteristics. Overall, the results in Table 1 indicate that the quotas altered the composition of the workforce by lowering the share of the workforce that is low-skilled.

To estimate the dynamic nature of quota exposure on population characteristics, we estimate an event study of the form given in Equation (3) where Y_{crt} captures an outcome for county c, belonging to region r, in year t. County fixed effects absorb time invariant county characteristics while region by year fixed effects control for differential time trends across regions.

$$\mathrm{Y}_{crt} = \beta_1 \mathbb{1}\{\mathrm{QE}_c\} + \beta_2 \left(\mathbb{1}\{\mathrm{QE}_c\} \times \sum_{j \neq 1920} \mathbb{1}\{t = j\} \right) + \gamma_c + \phi_{rt} + \varepsilon_{crt} \tag{3}$$

Figure 1 displays the point estimates and 95% confidence intervals when the low-skill share is the dependent variable[16]. From 1900-1910, there was an increase in the low-skill share for quota exposed counties. This is by construction, as counties with high quota exposure are going to be receiving more immigrants up until the implementation of the quota policies in the early 1920s. From 1910-1920, the low-skill share in quota exposed counties remains constant, likely the result of World War I (WWI) which led to a temporary

[15] The variable is "EDSCOR50" which is available in the IPUMS Full Count Censuses. Since the variable is based on occupation, the variable is only available for respondents who work

[16] Figure B.1 and Figure B.2 respectively display the results when the share of the population who are male, working age, newly arrived immigrants from a quota exposed country is the dependent variable and when the share of the population who is male, working age, and foreign born is the dependent variable.

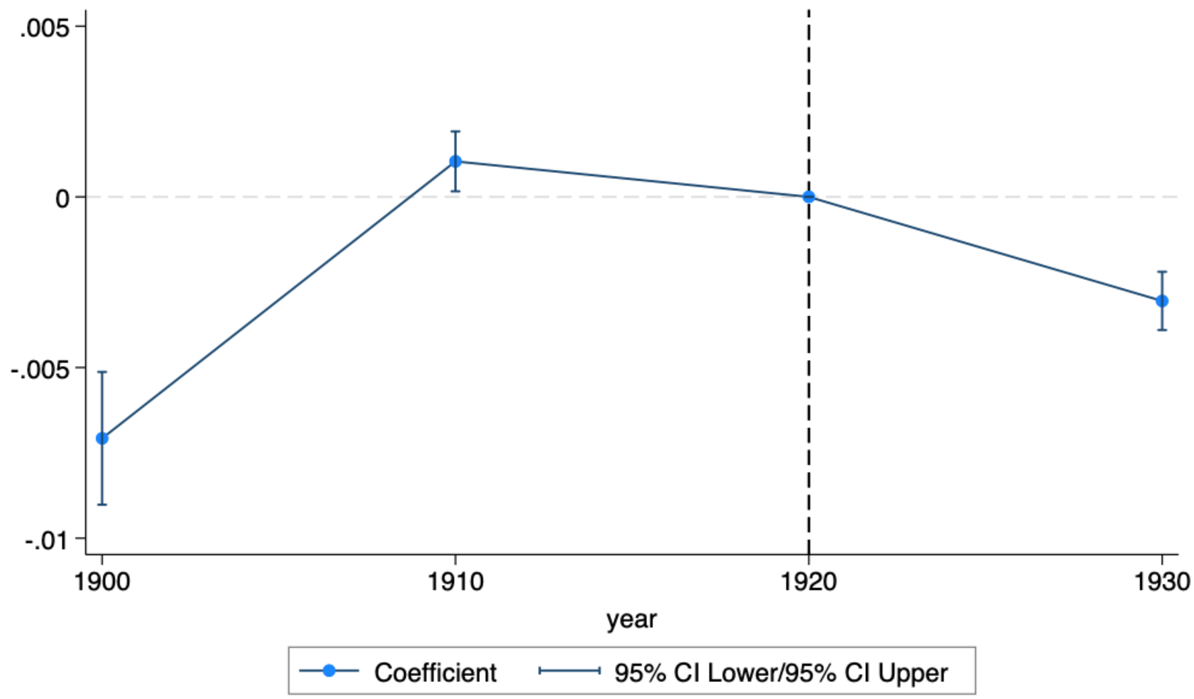
Table 1. Effect of Quotas on Population Characteristics

	Δ NI Share		Δ FB Share		Δ Low-Skill Share	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}\{\text{QE} > \text{p50}\} \times \mathbb{1}\{\text{Post}\}$	-0.004***	-0.003***	-0.006***	-0.004***	-0.006***	-0.004***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
$\mathbb{1}\{\text{QE} > \text{p50}\}$	0.000	0.000	-0.007***	-0.007***	0.003***	0.003***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
Urban Share $\times \mathbb{1}\{\text{Post}\}$		-0.001		-0.001		-0.007***
		(0.001)		(0.002)		(0.001)
Farm Share $\times \mathbb{1}\{\text{Post}\}$		0.001		0.010***		0.002**
		(0.001)		(0.001)		(0.001)
Mfn Share $\times \mathbb{1}\{\text{Post}\}$		-0.028**		-0.026**		-0.021***
		(0.012)		(0.013)		(0.004)
$\frac{\text{Mfn Value Add}}{\text{Worker}} \times \mathbb{1}\{\text{Post}\}$		-0.025***		-0.016		-0.033*
		(0.008)		(0.019)		(0.017)
$\bar{\text{Y}}$	.004	.004	.035	.035	.903	.903
%Δ From Mean	-94.7	-68	-17.1	-12.5	-.7	-.5
Region × Decade FE	✓	✓	✓	✓	✓	✓
N	7,902	7,902	7,902	7,902	7,902	7,902

Notes: This table presents regressions of various county population shares on quota exposure. Population shares are measured in 1900, 1910, 1920, and 1930. Counties are defined as being highly exposed to quotas if they have a quota exposure metric above the 50th percentile. Post is a dummy variable that takes the value of one for the 1920-1930 decadal change and is zero otherwise. In columns (1)-(2) the dependent variable is the decadal change in the share of the male working age population that has immigrated to the U.S. from a highly quota restricted country. In columns (3)-(4) the dependent variable is the decadal change in the share of the male working age population that is foreign born. In columns (5)-(6) the dependent variable is the decadal change in imputed low-skill employment share. Standard errors are clustered at the county level and shown in parentheses. * (p<0.1), ** (p<0.05), *** (p<0.01).

moratorium of immigration (Abramitzky et al. 2023). From 1920-1930 there is a decline in the low-skill share, consistent with the reduced amount of immigration for quota exposed counties relative to unexposed counties who continued to receive immigrants from Western Europe and other parts of the world that were not subject to quotas. The results in Figure 1 underscore the nature of the quota exposure shock. The upward trajectory that high quota exposure counties were on before the implementation of the quota policies was reversed by the quota policies.

Figure 1. Low-Skill Share



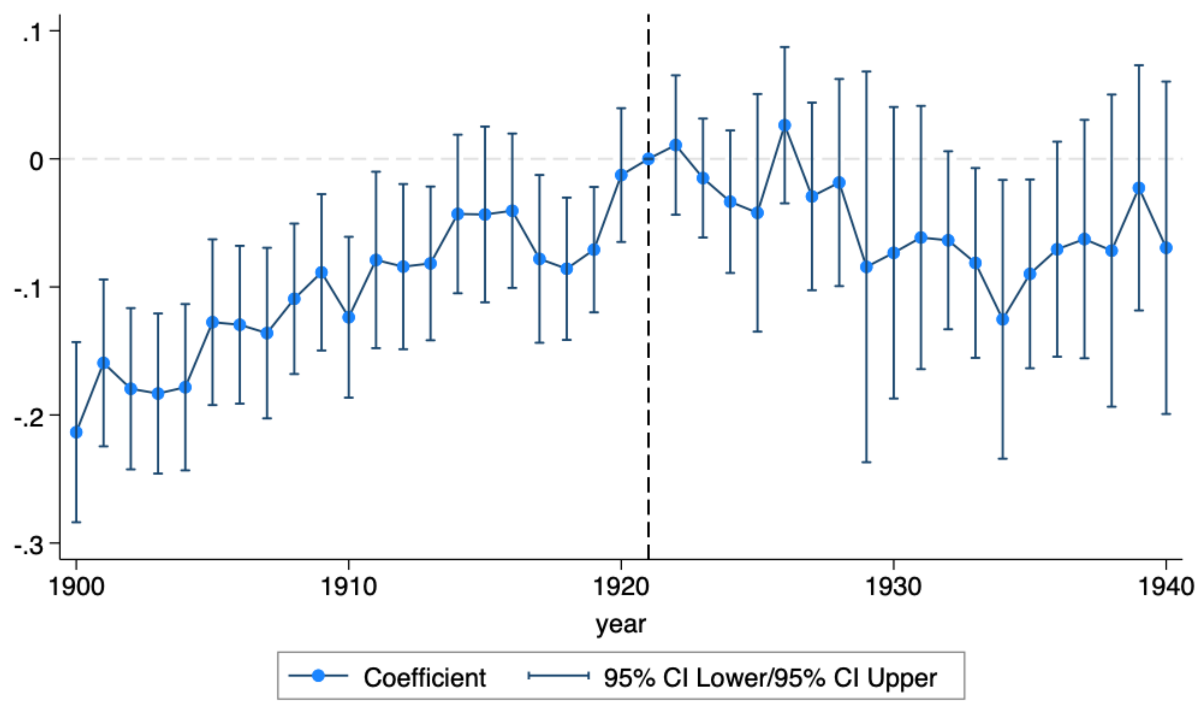
Notes: This figure presents point estimates and 95% confidence intervals from estimating Equation (3) with the imputed low-skill employment share as the dependent variable. Standard errors are clustered at the county level.

IV.II Innovation

IV.II.1 County Level

We start by exploring the dynamics of how quotas affected county level patenting using a standard event study framework outlined in Equation (3). Since we have annual data on county level patenting, we use 1921 as the omitted year and the dependent variable is patenting per thousand male working age individuals residing in the county in 1920. Figure 2 displays the point estimates and 95% confidence intervals from the estimation and reveals that from 1900-1921, the innovative activity of quota exposed counties was on a positive pre-trend, while after the implementation of the quotas, the trend flattens and then reverses. These results are expected if changes in the supply of low skilled labor are a key mechanism through which the quotas impacted innovation. Figure 1 shows that quota exposed counties had increasing low skill shares from 1900-1910 which then flattened and reversed with the advent of WWI and the implementation of quotas. If an abundance of low skilled labor encourages innovation, then we would expect a positive trend of innovation for quota exposed counties before the quotas were implemented and then a reversal of that trend after implementation of the quotas, which is what Figure 2 shows.

Figure 2. County Patenting



Notes: This figure presents point estimates and 95% confidence intervals from estimating Equation (3) with county patenting per one thousand male working age individuals residing in the county in 1920 as the dependent variable. The omitted year is 1921. Standard errors are clustered at the county level.

As Figure 2 shows that quota exposed counties were on a positive patenting trajectory prior to the implementation of quotas and then the trend subsequently flattens and reverses around 1921, a standard difference-in-differences in levels would lead to the conclusion that the quotas had a positive or insignificant impact on county innovation. This is because, on average, the coefficients are more negative from 1900-1920 compared to 1921-1940. Indeed, Table B.2 shows the results of a levels difference-in-difference estimation and reveals a positive, large, and statistically significant coefficient on the interaction between county quota exposure and a post dummy when no controls are used. But looking at Figure 2 it is clear that the quotas had a chilling effect on county innovation as the positive trend was halted and even reversed. It follows, then, that to provide an accurate estimate of the effect of quotas, relative to the counterfactual where the positive pre-trend continued, the outcome variable must be related to the trend, or change, in patenting in over time and not simply reflect the level of the variable.

To operationalize this, we estimate Equation (2) where the dependent variable is the change in decadal county patenting per thousand male working age individuals residing in the county in 1920. Patenting data is aggregated to the 1900, 1910, 1920, and 1930 decades[17], transformed into patenting per male working age individual, and then differenced across decades. We aggregate across decades instead of picking a year within the decade to get an accurate count of all patenting activity within the decade. For example, a county could be experiencing growth in the number of patents it applies for between 1900-1918 but apply for very few patents in 1919. If we looked at the change in patenting between the singular years of 1900 and 1919, we would see a decline in patenting, while differencing between the aggregate patenting in the 1900-1909 and 1910-1919 decades would account for 1919 as an abberation and yield the expected increase in patenting that took place between the two decades.

Table 2 shows the results. In column (1) we see that quota exposed counties were experiencing positive growth between the 1900 and 1910 decades as evidenced by the large and highly significant positive coefficient on the indicator of quota exposure. After the implementation of the quotas, this positive growth in patenting intensity reversed to become negative between the 1910 and 1920 and 1920 and 1930 decades as shown by the large, negative, and statistically significant coefficient on the interaction between quota exposure and a post quota dummy. These findings correspond with the reversal of the positive pre-trend, seen in our event study results. Column (1) estimates that highly quota exposed counties had lower patenting intensity of 0.72 relative to the counterfactual patenting intensity they would have had if the positive pre-trend would have continued unabated. This decline in patenting intensity of 0.72 amounts to a relative decline of 15%[18] off of mean levels. In column (2), we control for a county's 1920 urban, farmland, and manufacturing shares as well as manufacturing value added per manufacturing worker. These controls remove changes in trend due to these initial county characteristics, which may cause the patenting trend of counties to diverge for reasons other than quota exposure. Despite the addition of these controls, the interaction between quota exposure and a post dummy remains highly significant and large in economic magnitude. Column (3) tightens the specification further by adding county fixed effects. While a difference-in-difference in levels would include county fixed effects in all specifications to remove time-invariant level differences in county patenting intensity, our specification uses first differences across decades which removes level differences between the

[17]For example, the 1900 decade comprises the years 1900-1909, etc...

[18]This is calculated as $\frac{0.72}{4.763} \approx 15\%$

counties. In this case, the inclusion of county fixed effects removes average county trends in patenting growth and examines whether quotas led to deviations from average growth for counties. The point estimate of interest continues to be large and statistically significant. Overall, the results in Table 2 indicate that there was a meaningful negative reversal of trend in patenting for counties who were highly exposed to quotas.

IV.II.2 Inventor Level

While Section IV.II.1 provides evidence that quotas led to a decline in patenting intensity at the county level, they do not tell us about whether the decline in patenting is primarily due to faltering productivity for incumbent inventors or a dearth of new inventors. The decline in availability of low skilled immigrant labor may have affected the productivity of incumbents more as incumbents would have established expertise innovating in domains of knowledge which are complementary to the existence of low-skilled labor. On the other hand, it is likely that new inventors would have been more easily able to shift to new domains of innovation in response to the quota shock.

To estimate the dynamics of this effect, we use our panel of incumbent inventors who patent at least once prior to 1921 and aggregate the number of patents each inventor applies for by decade.[19] We winsorize decadal patenting at the 99.9% level (37 patents) to remove influence from extreme outliers. We estimate a version of Equation (3) with the level of incumbent inventor patenting (winsorized at the 99.9% level) in a given year as the dependent variable, the inclusion of inventor and region $\times$ year fixed effects, and the omitted year being 1921. Figure 3 displays the point estimates and 95% confidence intervals from the estimation and reveals that from 1900-1921, quota exposed incumbent inventors experienced increases in their patenting. After the quota shock arrived, the trend reverses with quota exposed inventors experiencing declines in their levels of patenting. This pattern of trend reversal at the time of the quotas is similar to the dynamics observed for both the low skill share of labor and county patenting intensity.

To arrive at an estimate of how much the decline in incumbent inventor productivity can account for the countywide aggregate effect, we estimate a version of Equation (2) with the decadal first difference of the winsorized number of patents applied for as the dependent variable. As before, we use first differences in patenting as the dependent variable to capture the trend break which occurred at the time the quotas were implemented. We also include a quartic in inventor age in all specifications to flexibly control for the age of the inventor. Creftbl$_{s}lides_{i}nv_{p}atpresentstheresultswithcolumn(1)showingthatincumbentinventorsresidinginquotaexp$

[19]The 1900 decade comprises the years 1900-1909. The 1910 decade comprises the years 1910-1919. The 1920 decade comprises the years 1920-1929. The 1930 decade comprises the years 1930-1939.

Table 2. Effect of Quotas on County Patenting

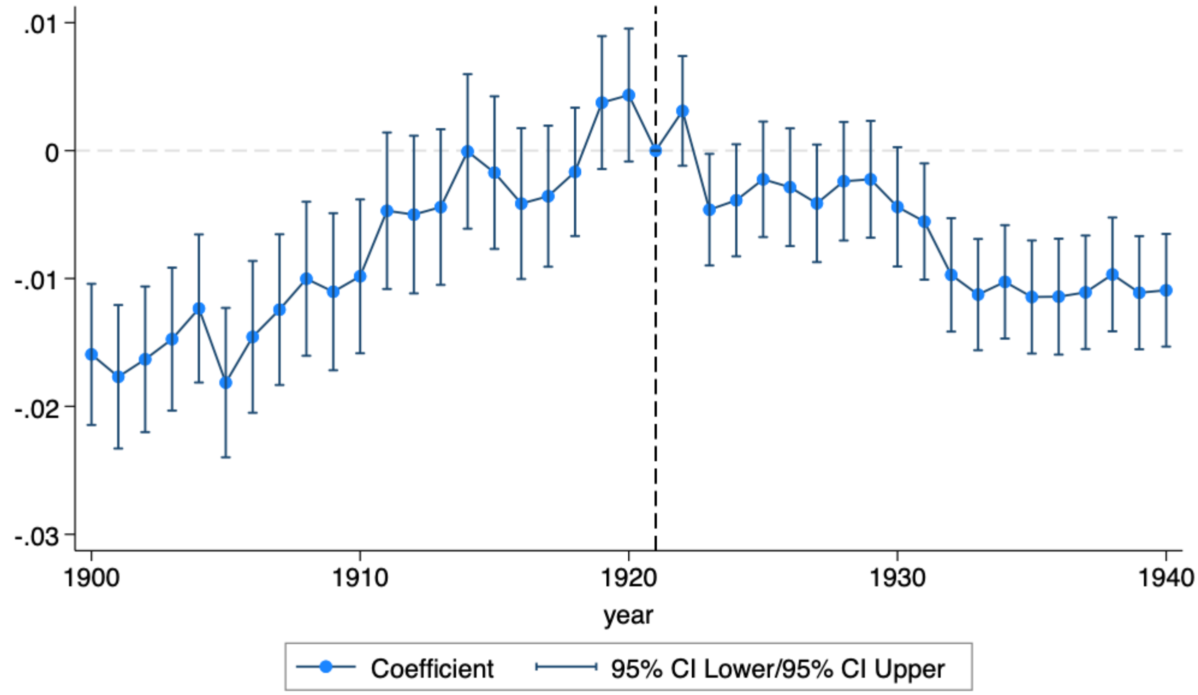
	$\Delta\frac{\text{Patent}}{\text{Pop}}$		
	(1)	(2)	(3)
$\mathbb{1}\{\text{QE} > \text{p50}\} \times \mathbb{1}\{\text{Post}\}$	-0.720***	-0.961***	-0.667***
	(0.238)	(0.233)	(0.243)
$\mathbb{1}\{\text{QE} > \text{p50}\}$	0.868***	0.868***	
	(0.157)	(0.157)	
Urban Share $\times$ $\mathbb{1}\{\text{Post}\}$		2.617***	2.164
		(0.977)	(1.497)
Farm Share $\times$ $\mathbb{1}\{\text{Post}\}$		0.586	2.856
		(1.354)	(1.918)
Mfn Share $\times$ $\mathbb{1}\{\text{Post}\}$		-3.450	-4.526
		(8.338)	(13.372)
$\frac{\text{Mfn Value Add}}{\text{Worker}} \times \mathbb{1}\{\text{Post}\}$		-0.637	-7.159
		(3.418)	(7.570)
$\overline{\frac{\text{Patent}}{\text{Pop}}}$	4.763	4.763	4.763
Region $\times$ Decade FE	✓	✓	✓
County FE			✓
N	7,902	7,902	7,902

Notes: This table presents regressions of county patenting on quota exposure. Counties are defined as being highly exposed to quotas if they have a quota exposure metric above the 50th percentile. Post is a dummy variable that takes the value of one for the changes between 1910-1919 versus 1920-1929 and the changes between 1920-1929 versus 1930-1939. A county $\times$ year observation receives one patent for each patent application having at least one inventor residing in the county. County $\times$ year patents are aggregated to the 1900, 1910, 1920, and 1930 decades where the 1900 decade comprises the years 1900-1909, etc... The dependent variable in all columns is the decadal change in aggregate county patenting, scaled by thousands of male working age population residing in the county in 1920. Standard errors are clustered at the county level and shown in parentheses. * ($p<0.1$), ** ($p<0.05$), *** ($p<0.01$).

trendofpatentingrelativetounexposedinventors, beforetheimplementationofthequotas, asevidencedbythe

[20]This is calculated as $\frac{0.138}{0.721} \approx 19\%$

Figure 3. Inventor Patenting



Notes: This figure presents the point estimates and 95% confidence intervals from regressions of the form in Equation (3). The dependent variable is the amount of patents applied for in a year winsorized at the 99.9 percentile. Inventors are defined as being highly exposed to quotas if in the 1920 Census they resided in a county having a quota exposure metric above the 50th percentile. A quartic in age, region × decade fixed effects, and inventor fixed effects are included. Standard errors are clustered at the inventor level.

$trendcontinuing.Column(2)addscontrolswhichdoesnotmateriallyaffecttheresults.Column(3)addsinven$

IV.II.3 Firm Level

We next take our analysis to the firm level where we examine the response of firms to the quotas. This will allow us to more directly test whether the scale of a firm's manufacturing operation is a mechanism through which the quotas impacted innovative activity. Further, firms have the ability to respond to the quota shocks in a way that counties and inventors cannot. For example, firms facing the loss of low-skilled immigrant labor may move their production to regions of the country less affected by quotas.

To estimate the dynamic effect that quotas had on firm patenting activity we estimate versions of Equation (3) at the firm × decade level with firm and decade fixed effects. We estimate the firm event studies at the decade level, as opposed to the annual level

[21] This is calculated as $\frac{0.076}{0.721} \approx 11\%$

Table 3. Effect of Quotas on Inventor Patenting

	ΔPatents		
	(1)	(2)	(3)
$\mathbb{1}\{QE > p50\} \times \mathbb{1}\{Post\}$	-0.137***	-0.133***	-0.076***
	(0.019)	(0.019)	(0.022)
$\mathbb{1}\{QE > p50\}$	0.109***	0.109***	
	(0.014)	(0.014)	
Urban Share $\times\ \mathbb{1}\{Post\}$		-0.005	-0.070**
		(0.013)	(0.034)
Farm Share $\times\ \mathbb{1}\{Post\}$		-0.003	0.024
		(0.014)	(0.036)
Mfn Share $\times\ \mathbb{1}\{Post\}$		-0.041	-0.170
		(0.069)	(0.179)
$\frac{\text{Mfn Value Add}}{\text{Worker}} \times \mathbb{1}\{Post\}$		0.029	-0.048
		(0.363)	(0.930)
$\overline{\text{Patents}}$	.721	.721	.721
Region $\times$ Decade FE	✓	✓	✓
Inventor FE			✓
N	530,640	530,640	530,640

Notes: This table presents regressions of inventor patenting on quota exposure. Inventors are defined as being highly exposed to quotas if in the 1920 Census they resided in a county having a quota exposure metric above the 50th percentile. Post is a dummy variable that takes the value of one for the changes between 1910-1919 versus 1920-1929 and the changes between 1920-1929 versus 1930-1939. Inventor patenting is aggregated to the 1900, 1910, 1920, and 1930 decades where the 1900 decade comprises the years 1900-1909 etc... The amount of patenting in a decade is winsorized at the 99.9 percentile. The dependent variable in all columns is the decadal change in aggregate inventor patenting. A quartic in age is included in all specifications and standard errors are clustered at the inventor level and shown in parentheses. * ($p<0.1$), ** ($p<0.05$), *** ($p<0.01$).

because we have significantly fewer firms than we do counties or individual inventors.[22] The dependent variable is the inverse hyberbolic sine of patenting in the decade and observations are weighted by the number of patents the firm applied for in the pre-quota time period.

[22] There 373 firms, 2,804 counties, and 185,324 inventors in the data.

Figure 4 plots the resulting point estimates and 95% confidence intervals on the quota exposure × decade dummies. The results indicate that heading into the implementation of the quotas, firms who would face large quota exposure were increasing their patenting by more than firms who would be less exposed to quotas. After the quotas were implemented, the trend reverses with quota exposed firms decreasing their patenting significantly relative to firms that were less exposed. These dynamics follow a similar pattern to what we have seen before in our analysis of the low-skill population share and the innovative activity at the county or inventor levels. As a result, it will be important to look for changes in trend when estimating our difference-in-differences specifcations.

Figure 4. Firm Patenting

Notes: This figure presents the point estimates and 95% confidence intervals from regressions of the form in Equation (3). The dependent variable is the inverse hyperbolic sine of patents applied for in a decade. Firm and decade fixed effects are included and standard errors are clustered at the firm level.

To examine the average firm response, we estimate specifications of the variety outlined in Equation (2) but where the unit of analysis is the firm instead of the county and region × time period fixed effects are replaced with time period or time period × industry fixed effects. As our dependent variable, we use the Davis, Haltiwanger, and Schuh (DHS) growth rate[23] of the number of patents applied for between two decades. The DHS growth rate is

[23]This is calculated as $\frac{Y_1 - Y_0}{\frac{Y_1 + Y_0}{2}}$.

well suited for our situation for several reasons. First, it captures the change in patenting activity over time which, given the evidence in Figure 4, is needed for an accurate measure of how quota exposure impacted innovative activity. Second, the DHS growth rate is not undefined when a firm has an extensive margin change[24] in patenting activity. As in Autor et al. 2020, we weight observations by the average patenting in the current and next decade.

Table 4 presents the results with column (1) showing that firms who were above the median in quota exposure saw a large decline in patenting after the implementation of quotas. In column (2), we effectively limit comparisons to be within industry by replacing decade fixed effects with industry $\times$ decade fixed effects. This removes any differential change in growth between industries that could be correlated with quota exposure. Limiting comparisons to be within industry does not materially affect the estimated impact of quotas on patenting activity. Column (4) is our tightest specification, where controls are added and firm fixed effects remove average patenting growth rates of firms. Our coefficient of interest remains precisely estimated and large in magnitude. These results indicate that firms follow the way of counties and inventors, they reduce their patenting in response to the implementation of the quotas.

Next, we examine whether the effect of quota exposure is concentrated on firms who have large scales of manufacturing activity and thus employ a significant amount of labor. This is an important check of our proposed mechanism through which the quotas affect innovative activity. If innovative activity is reliant on a steady supply of low skilled labor, then we would expect firms who need more low skilled labor to disproportionately decrease their innovation in response to the quotas. In contrast, other potential mechanisms are unlikely to exert this differential effect. To measure whether a firm needs a large amounts of workers at its factories, we aggregate the number of wage earners the firm employs across all its establishments and then scale by the number of establishments the firm has. Firms above the 50th percentile in workers per establishment are indicated as having a high level of workers per establishment. To test whether firms who employ larger amounts of workers at their establishments are more responsive to quota exposure and the subsequent decline in the low skill share, we interact this indicator of high levels of workers per establishment with the quota exposure indicator and post dummy.

Table 5 shows the results. Starting in column (2) when industry $\times$ decade fixed effects are included, we see that the point estimate on the interaction between high worker per establishment and post-quota exposure is negative and statistically significant. Further, across all the specifications the interaction between quota exposure and a post dummy is no

[24] An extensive margin change occurs when a firm has zero patenting in one decade and positive patenting in the following or prior decade. An extensive margin change occurs in 38% of the observations

Table 4. Effect of Quotas on Firm Patenting

	DHS % Δ Patents			
	(1)	(2)	(3)	(4)
$\mathbb{1}\{QE > p50\} \times \mathbb{1}\{Post\}$	-1.154***	-1.139***	-1.288***	-1.129***
	(0.396)	(0.436)	(0.424)	(0.297)
$\mathbb{1}\{QE > p50\}$	0.755**	0.726**	0.726**	
	(0.313)	(0.332)	(0.333)	
Urban Share $\times \mathbb{1}\{Post\}$			-0.350	-0.077
			(0.363)	(0.915)
Farm Share $\times \mathbb{1}\{Post\}$			-0.338	-0.409
			(0.322)	(0.746)
Mfn Share $\times \mathbb{1}\{Post\}$			2.753*	11.066***
			(1.536)	(2.692)
$\frac{\text{Mfn Value Add}}{\text{Worker}} \times \mathbb{1}\{Post\}$			16.562	-63.766*
			(16.105)	(37.903)
Decade FE	✓			
Industry × Decade FE		✓	✓	✓
Firm FE				✓
N	989	989	989	989

Notes: This table presents regressions of firm patenting on quota exposure. Firms are defined as being highly exposed to quotas if the firm has a quota exposure metric above the 50th percentile. A firm's quota exposure metric is calculated by taking the employment weighted quota exposure metric of the firm's establishments in the 1929 CoM where the establishment's quota exposure metric is based on the county the establishment is located in. Post is a dummy variable that takes the value of one for the changes between 1910-1919 versus 1920-1929 and the changes between 1920-1929 versus 1930-1939. Firm patenting is aggregated to the 1900, 1910, 1920, and 1930 decades where the 1900 decade comprises the years 1900-1909 etc... The dependent variable in all columns is the decadal DHS growth rate in aggregate firm patenting. Observations are weighted by the average number of patents between the starting and ending decade. Standard errors are clustered at the firm level and shown in parentheses. * (p<0.1), ** (p<0.05), *** (p<0.01). * (p<0.1), ** (p<0.05), *** (p<0.01).

longer statistically significant, showing that the entire negative effect of quota exposure on patenting is loaded on firms with above median levels of workers per establishment. This result provides evidence that firms who relied on large amounts of labor to mass produce their output were disproportionately affected by the quotas as they had less access to the low-skilled labor needed in their plants.

Table 5. Effect of Quotas on Firm Patenting

	DHS % Δ Patents			
	(1)	(2)	(3)	(4)
$\mathbb{1}\{\text{QE} > \text{p50}\} \times \mathbb{1}\{\text{Post}\} \times \mathbb{1}\{\frac{\text{Worker}}{\text{Plant}} > \text{p50}\}$	-0.733	-1.053**	-1.064**	-0.832**
	(0.616)	(0.492)	(0.490)	(0.374)
$\mathbb{1}\{\text{QE} > \text{p50}\} \times \mathbb{1}\{\text{Post}\}$	-0.543	-0.318	-0.416	-0.482
	(0.471)	(0.346)	(0.354)	(0.321)
$\mathbb{1}\{\text{QE} > \text{p50}\}$	0.504**	0.419	0.419	
	(0.243)	(0.296)	(0.297)	
Urban Share $\times \mathbb{1}\{\text{Post}\}$			-0.522	-0.553
			(0.389)	(0.848)
Farm Share $\times \mathbb{1}\{\text{Post}\}$			-0.463*	-0.884
			(0.270)	(0.614)
Mfn Share $\times \mathbb{1}\{\text{Post}\}$			1.602	7.751***
			(1.348)	(2.335)
$\frac{\text{Mfn Value Add}}{\text{Worker}} \times \mathbb{1}\{\text{Post}\}$			17.433	-45.836
			(13.890)	(30.201)
Decade FE	✓			
Industry × Decade FE		✓	✓	✓
Firm FE				✓
N	989	989	989	989

Notes: This table presents regressions of firm patenting on quota exposure. Firms are defined as being highly exposed to quotas if the firm has a quota exposure metric above the 50th percentile. A firm's quota exposure metric is calculated by taking the employment weighted quota exposure metric of the firm's establishments in the 1929 CoM where the establishment's quota exposure metric is based on the county the establishment is located in. Post is a dummy variable that takes the value of one for the changes between 1910-1919 versus 1920-1929 and the changes between 1920-1929 versus 1930-1939. Firm patenting is aggregated to the 1900, 1910, 1920, and 1930 decades where the 1900 decade comprises the years 1900-1909 etc... The dependent variable in all columns is the decadal DHS growth rate in aggregate firm patenting. Large establishment firms are defined as firms who have above the 50th percentile in 1929 workers per establishment. Observations are weighted by the average number of patents between the starting and ending decade. Standard errors are clustered at the firm level and shown in parentheses. * ($p<0.1$), ** ($p<0.05$), *** ($p<0.01$). * ($p<0.1$), ** ($p<0.05$), *** ($p<0.01$).

IV.III Firm Response

Given that quota exposure had a negative effect on the innovative output of affected firms, we next examine the response of firms to quota exposure. If firms face significant mobility frictions, then it is possible that firms will not adjust in response to the quota shock, but if the mobility frictions are not prohibitively large then we would expect to see firms move their production away from quota exposed areas to gain more access to low-skilled labor.

To examine whether firms reallocate their production facilities, we need to measure the location of a firm's production both before and after the quotas were implemented. To measure the location of a firm's production continuously from 1900-1940 we turn to patent data, as there is no CoM data from 1900-1928, and we calculate the quota exposure that a firm faces based on the location of its patenting activity. Specifically, for each patent belonging to a firm in our 1929 CoM data, we calculate the quota exposure of each inventor $\times$ patent pair based on the county of residence of the inventor. Using these observations, we then calculate the average quota exposure for each firm $\times$ year observation which gives us a time varying measure of how exposed the firm is to quotas.

The ability of this measure to capture the time varying amount of quota exposure a firm's production facilities face is directly related to the extent that inventor locations proxy for the production locations of the firm. To examine whether patenting activity is highly correlated with manufacturing locations, we calculate for each firm the share of its 1929 patents which are within 10 miles of one of the firm's manufacturing plants. The median share of a firm's patenting activity that is within 10 miles of an establishment is 92%[25]. Despite this, there are some firms where a sizable portion of patenting activity is further than 10 miles away from a manufacturing establishment. To ensure that patenting provides a good proxy for the manufacturing locations of the firm, we remove firms who have less than 70% of their 1929 patents located within 10 miles of an establishment as patenting activity. Further, firms who do not patent in 1929 are removed as we have no way to measure whether patent locations provide a good measure of manufacturing plant locations. After making these restrictions, we are left with 95 firms and the average firm has 96%[26] of its patents located within 10 miles of one of its manufacturing establishments. These results indicate that for the sample of firms we have selected, patenting provides a good proxy for the location of the firm's production facilities.

With this time varying measure of quota exposure facing the firm, we examine whether

[25] If we weight by the number of patents the firm applied for in 1929, the median share of a firm's patenting activity that is within 10 miles of an establishment is 74%.

[26] If we weight by the number of patents the firm applied for in 1929, then the average firm has 86% of its patents located within 10 miles of one of its manufacturing establishment.

higher quota exposure in 1929[27] leads firms to move their production away from quota exposed locations by estimating event study specifications of a similar form as what was used to create Figure 4 but with the level of time-varying decadal quota exposure of the firm as the dependent variable. The results show an upward trend heading into the implementation of the quotas with firms who would have high quota exposure increasingly moving their production to areas with higher quota exposure. This aligns with the expectation that prior to the implementation of quotas, firms who required large amounts of low-skilled immigrant labor were moving their manufacturing facilities to areas who received large flows of low-skilled immigrant labor. The effect of the quota implementation on the quota exposure a firm faces is slow to materialize with no change in quota exposure between the 1910-1919 and 1920-1929 decades. However, in the 1930-1939 decade, quota exposed firms move their production to areas which are less quota exposed relative to unexposed firms. The slow response of firms to quota exposure is consistent with the presence of significant frictions present in the process of reallocating production to more suitable locations.

We now estimate the average effect of quotas by estimating similar specifications as used to create Table 4 but with the change in quota exposure as the dependent variable instead of the DHS growth of patents. Table 6 presents the results with column (1) showing that after the implementation of quotas, firms who were more exposed to quotas moved their patenting and production to counties less exposed to quotas. In columns (2) and (3) we respectively add industry × decade fixed effects and firm fixed effects which reduces the precision of our estimate and attenuates the estimate towards zero.

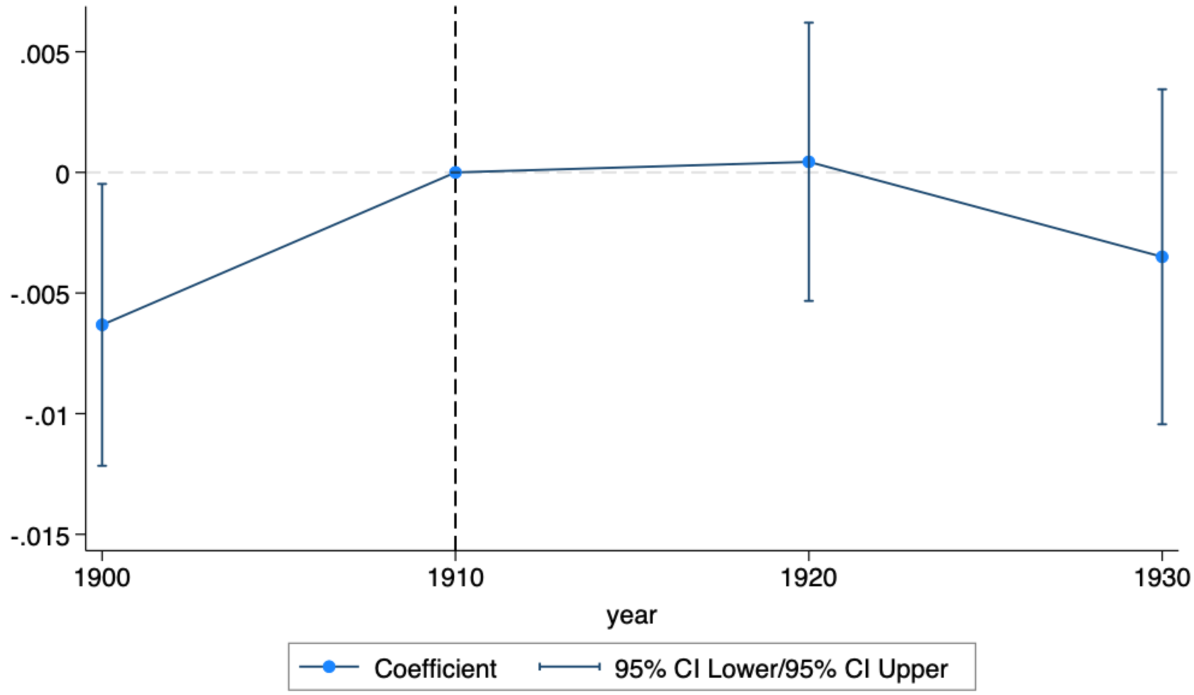
In columns (4)-(6) we examine whether firms with large workforces moved away from quota exposed geographies relatively more. Across columns (4)-(6), we find that firms with high worker to establishment ratios decrease their quota exposure after the shock by around 20-40% off of mean levels. These results indicate that firms who had sufficient need for large amounts of labor at their establishments did respond to the quotas by moving their production to areas where they could have easier access to low-skilled immigrant labor. The analysis provides evidence that the need for large amounts of labor necessary in mass production is an important mechanism at play in the firm's decision to relocate their production to areas with greater incoming flows of immigrants.

V Conclusion

In this paper, we explore the effects of low-skilled immigrants on U.S. invention in the early twentieth century, uncovering a complementarity between the scale of labor available

[27]Quota exposure in 1929 is still calculated using the CoM establishment level data.

Figure 5. Firm QE



Notes: This figure presents the point estimates and 95% confidence intervals from regressions of the form in Equation (3). The dependent variable is the imputed quota exposure a firm faces in a decade based on the location of their patenting activity. Firm and decade fixed effects are included and standard errors are clustered at the firm level.

for production and patented inventions at that time. We make three main contributions: (1) We show that a reduction in low-skilled labor can negatively affect invention; (2) we show that this effect can occur at multiple levels, including individuals, firms, and locations; and (3) we show that this effect is driven by inventions associated with firms that have large establishment sizes.

These results have implications for several literatures. First, in the process of making the above contributions, we show that, in spite of adjustments by native labor (Abramitzky et al. 2023), the reduction in low-skilled immigration to quota-exposed locations did decrease the fraction of the workforce that was low-skilled; adjustments by native labor were not sufficient to completely reverse the effects of the quota on skill composition. Second, our results suggest that the long-running question of how labor scarcity affects innovation cannot be sufficiently determined by the classical and intuitive arguments in (Hicks 1932) and (Habakkuk 1962). More complete models such as (Acemoglu 2010) are needed to begin relating labor scale in production to the marginal product of labor. As we explain above, our finding that scarce

Table 6. Effect of Quotas on Firm Geographic Mobility

	ΔQE					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}\{\text{QE}\} \times \mathbb{1}\{\text{Post}\} \times \mathbb{1}\{\frac{\text{Worker}}{\text{Plant}} > \text{p50}\}$				-0.027**	-0.020*	-0.045*
				(0.011)	(0.011)	(0.026)
$\mathbb{1}\{\text{QE}\} \times \mathbb{1}\{\text{Post}\}$	-0.008*	-0.005	0.004	0.018*	0.015	0.049
	(0.004)	(0.006)	(0.010)	(0.010)	(0.013)	(0.030)
$\mathbb{1}\{\text{QE}\}$	0.006**	0.003		-0.015***	-0.015**	
	(0.003)	(0.004)		(0.003)	(0.007)	
Urban Share $\times$ $\mathbb{1}\{\text{Post}\}$	0.014	0.015	0.016	0.016	0.015	0.057
	(0.014)	(0.020)	(0.060)	(0.014)	(0.020)	(0.061)
Farm Share $\times$ $\mathbb{1}\{\text{Post}\}$		-0.001	0.032	0.001	-0.001	0.055
	(0.011)	(0.012)	(0.048)	(0.012)	(0.013)	(0.054)
Mfn Share $\times$ $\mathbb{1}\{\text{Post}\}$	-0.042	-0.068	-0.215	-0.041	-0.065	-0.136
	(0.040)	(0.062)	(0.151)	(0.042)	(0.062)	(0.136)
$\frac{\text{Mfn Value Add}}{\text{Worker}} \times \mathbb{1}\{\text{Post}\}$	0.061	0.285	-0.308	0.079	0.317	-0.781
	(0.327)	(0.416)	(0.797)	(0.337)	(0.411)	(0.881)
$\overline{\text{QE}}$	.11	.11	.11	.11	.11	.11
Decade FE	✓			✓		
Industry $\times$ Decade FE		✓	✓		✓	✓
Firm FE			✓			✓
N	196	193	193	196	193	193

Notes: This table presents regressions of the evolution of a firm's dynamic quota exposure on their initial static quota exposure. Firms are defined as being highly exposed to quotas if the firm has a quota exposure metric above the 50th percentile. A firm's quota exposure metric is calculated by taking the employment weighted quota exposure metric of the firm's establishments in the 1929 CoM where the establishment's quota exposure metric is based on the county the establishment is located in. Post is a dummy variable that takes the value of one for the changes between 1910-1919 versus 1920-1929 and the changes between 1920-1929 versus 1930-1939. The dependent variable in all columns is the decadal change in a firm's dynamic quota exposure. A firm's dynamic quota exposure in a year is calculated as the average quota exposure of a firm's patents based on the county the inventors are located in. A firm's dynamic quota exposure in a decade is calculated as the firm's average annual dynamic quota exposure across the years in the decade. Only firms where weakly more than 70 percent of their 1929 patents are located within 10 miles of an establishment are included in the sample. Large establishment firms are defined as firms who have above the 50th percentile in 1929 workers per establishment. Observations are weighted by the average number of patents between the starting and ending decade. Standard errors are clustered at the firm level and shown in parentheses. * ($p<0.1$), ** ($p<0.05$), *** ($p<0.01$). * ($p<0.1$), ** ($p<0.05$), *** ($p<0.01$).

labor leads to fewer patented innovations by firms with large establishment sizes is consistent with a broad literature showing that the elasticity of substitution between capital and labor is less than one (see (Hamermesh 1993), (Chirinko 2008), (Antràs 2004), (Oberfield and Raval 2021), as well as a world in which large establishments in particular make heavy use of technology embodied in capital.

Future work can explore the effect of the decline in the low-skilled workforce on the direction of inventive activity. It is possible that America's shift away from innovations relevant for large-scale manufacturing and towards innovations useful for firms with smaller establishment sizes began during this era. Given that the innovative ecosystems in the US today are potentially less focused on large scale manufacturing, it is possible that a reduction in low-skilled migration may not have the same effect on innovation as we found in the context of the 1920s. More work examining how economic conditions moderate the effect of low skilled migration on innovation would be an important contribution.

A Firm to Patent Matching

For each CoM firm name x PATSTAT firm name pair, we calculate the simple Levenshtein ratio[28] and the partial Levenshtein ratio, which differs from the simple Levenshtein ratio in that it checks each substring in the shorter string against all same length substrings of the larger string and only keeps the highest score for each substring in the shorter string. The partial ratio will capture an exact match even when one string has extra words added. For both the simple and partial ratios, we also estimate the "token sorted" versions where the strings to be matched are both sorted so that tokens are in alphabetical order. This ensures that "FORD MOTOR" and "MOTOR FORD" would match. Finally, the "token set" versions start with the intersection of the two strings, ensuring that "COMPANY FORD MOTOR" and "FORD MOTOR" would be exact matches. We consider a CoM firm name and a PATSTAT firm name to match if any one of the following conditions hold

- Simple Levenshtein Ratio $\geq$ 90%
- Simple Levenshtein Ratio $\geq$ 85% AND Partial Levenshtein Ratio $\geq$ 85% AND Simple Levenshtein Token Sort Ratio $\geq$ 85% AND Simple Levenshtein Token Set Ratio $\geq$ 85% AND Partial Levenshtein Token Sort Ratio $\geq$ 90%
- Simple Levenshtein Ratio $\geq$ 75% AND Partial Levenshtein Ratio = 100%
- Simple Levenshtein Ratio $\geq$ 65% AND Partial Levenshtein Token Sort Ratio $\geq$ 90% AND Simple Levenshtein Token Set Ratio = 100%

B Additional Results

B.I Population Characteristics

B.II County Level

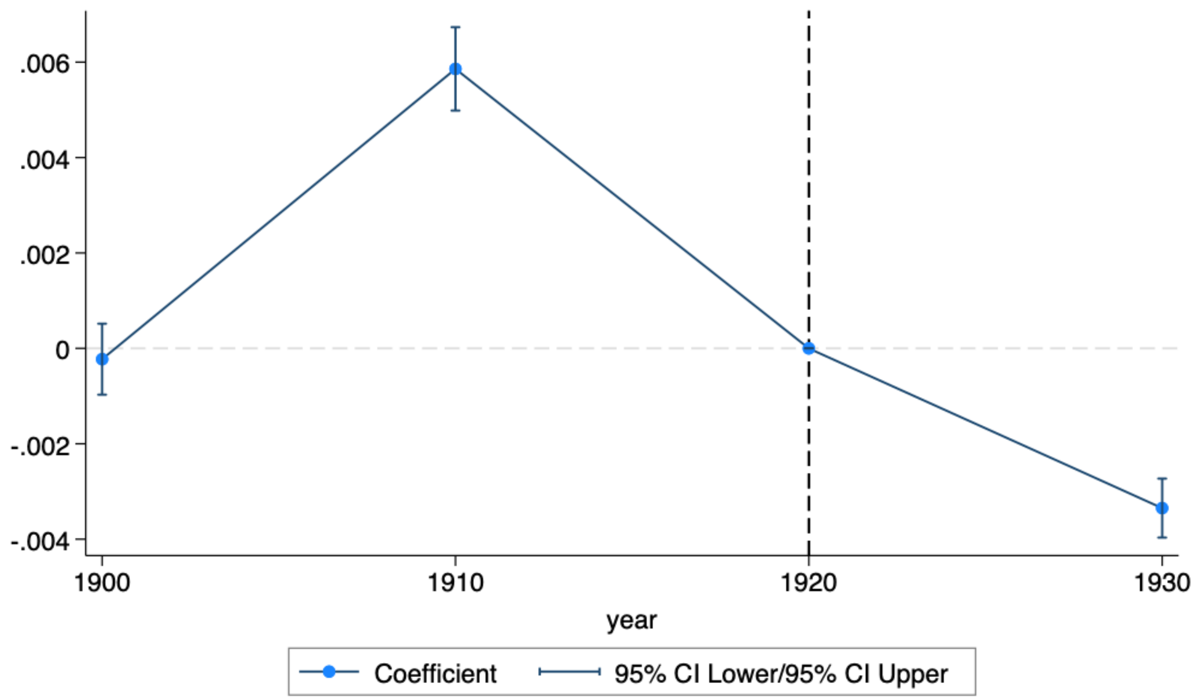
[28] The minimum number of edits required to make the strings identical as a share of the number of tokens in the string

Table B.1. Effect of Quotas on Population Characteristics with County FE

	(1) Δ NI Share	(2) Δ FB Share	(3) Δ Low-Skill Share
$\mathbb{1}\{QE > p50\} \times \mathbb{1}\{Post\}$	-0.002***	-0.004***	-0.002**
	(0.000)	(0.001)	(0.001)
Urban Share $\times$ $\mathbb{1}\{Post\}$	-0.001	-0.004	-0.017***
	(0.002)	(0.003)	(0.002)
Farm Share $\times$ $\mathbb{1}\{Post\}$	-0.001	0.002	0.004**
	(0.001)	(0.002)	(0.002)
Mfn Share $\times$ $\mathbb{1}\{Post\}$	-0.043**	-0.053***	-0.078***
	(0.017)	(0.020)	(0.012)
$\frac{\text{Mfn Value Add}}{\text{Worker}} \times \mathbb{1}\{Post\}$	-0.024*	0.008	-0.017
	(0.013)	(0.022)	(0.026)
$\overline{Y}$	.004	.035	.903
%Δ From Mean	-60.2	-11.4	-.2
Region × Decade FE	✓	✓	✓
County FE	✓	✓	✓
N	7,902	7,902	7,902

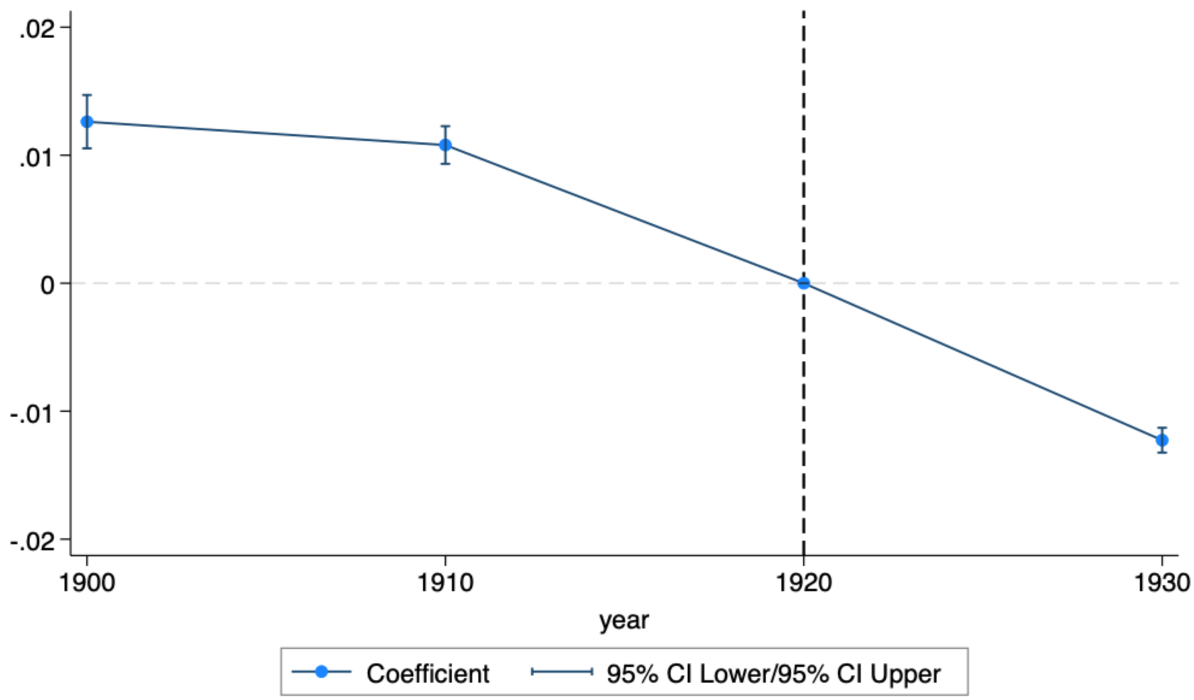
Notes: This table presents regressions of various county population shares on quota exposure. Population shares are measured in 1900, 1910, 1920, and 1930. Counties are defined as being highly exposed to quotas if they have a quota exposure metric above the 50th percentile. Post is a dummy variable that takes the value of one for the 1920-1930 decadal change and is zero otherwise. In column (1) the dependent variable is the decadal change in the share of the male working age population that has immigrated to the U.S. from a highly quota restricted country. In column (2) the dependent variable is the decadal change in the share of the male working age population that is foreign born. In column (3) the dependent variable is the decadal change in imputed low-skill employment share. Standard errors are clustered at the county level and shown in parentheses. * ($p<0.1$), ** ($p<0.05$), *** ($p<0.01$).

Figure B.1. New Immigrant Share



Notes: This figure presents the point estimates and 95% confidence intervals from regressions of the form in Equation (3). The dependent variable is the share of the population what are newly immigrated working age men from a quota exposed country. Standard errors are clustered at the county level.

Figure B.2. Foreign Born Share



Notes: This figure presents the point estimates and 95% confidence intervals from regressions of the form in Equation (3). The dependent variable is the share of the male working age population what are foreign born. Standard errors are clustered at the county level.

Table B.2. Level Difference-in-Differences Estimate of the Effect of Quotas on County Patenting

	$\Delta \frac{\text{Patent}}{\text{Pop}}$	
	(1)	(2)
$\mathbb{1}\{\text{QE} > \text{p50}\} \times \mathbb{1}\{\text{Post}\}$	0.910***	0.220
	(0.245)	(0.246)
$\mathbb{1}\{\text{QE} > \text{p50}\}$		
Urban Share $\times\ \mathbb{1}\{\text{Post}\}$		5.403***
		(1.417)
Farm Share $\times\ \mathbb{1}\{\text{Post}\}$		0.102
		(1.967)
Mfn Share $\times\ \mathbb{1}\{\text{Post}\}$		-4.122
		(12.028)
$\frac{\text{Mfn Value Add}}{\text{Worker}} \times \mathbb{1}\{\text{Post}\}$		7.149
		(6.421)
$\overline{\frac{\text{Patent}}{\text{Pop}}}$	4.99	4.99
Region × Decade FE	✓	✓
County FE	✓	✓
N	10,536	10,536

Notes: This table presents regressions of county patenting on quota exposure. Counties are defined as being highly exposed to quotas if they have a quota exposure metric above the 50th percentile. Post is a dummy variable that takes the value of one for the 1920-1929 and 1930-1939 decades. A county × year observation receives one patent for each patent application having at least one inventor residing in the county. County × year patents are aggregated to the 1900, 1910, 1920, and 1930 decades where the 1900 decade comprises the years 1900-1909, etc... The dependent variable in all columns is the decadal level of aggregate county patenting, scaled by thousands of male working age population residing in the county in 1920. Standard errors are clustered at the county level and shown in parentheses. * ($p<0.1$), ** ($p<0.05$), *** ($p<0.01$).