The Social Consequences of Technological Change: Evidence from U.S. Electrification and Immigrant Labor

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Abstract

This paper examines how technological change in production processes affects social cohesion in ethnically diverse societies. I study the early expansion of the electric grid in the United States between 1900 and 1940, when electrification transformed manufacturing and large-scale immigration reshaped the labor force. Using newly digitized maps of the U.S. high-voltage transmission network linked to full-count census data, I exploit the staggered rollout of electrification across counties to estimate its causal effects on the integration of immigrant and native workers. Electrified industries became more diverse and less segregated along ethnic lines. These effects extend beyond the workplace. Electrification is associated with lower residential segregation among manufacturing workers and a partial attenuation of the negative relationship between immigrant presence and local public service provision. Overall, I find that, in this context, technological change reshaped the social fabric by promoting integration both at work and within local communities.

Keywords: Technological Change, Social Cohesion, Electrification, Immigration, Manufacturing. **JEL Codes:** J15, J61, O33, N32, R23.

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1 Introduction

Technological change drives economic growth by introducing more efficient means of production. In addition to economic effects, technological transformations can also have profound social consequences. Innovations that alter production processes, in particular, can reshape how firms are organized, how people work, and how they interact within their communities (Tönnies, 1887; Durkheim, 1893; Weber, 1922). A priori, however, it is unclear whether such changes reinforce existing social divisions or foster greater cohesion. Understanding this relationship is especially important in culturally diverse societies, where social cohesion may be important for growth but is challenging to achieve (Alesina et al., 1999; Alesina & La Ferrara, 2000; Easterly et al., 2006). This paper studies how technological change in production processes affects the social cohesion of ethnically diverse societies.

I explore this relationship in the context of the early expansion of the electric grid in the United States between 1900 and 1940. Electrification was the pivotal technological change of the Second Industrial Revolution, and fundamentally transformed production processes in manufacturing (David, 1990). This transformation unfolded during a period of remarkable cultural heterogeneity in the U.S., shaped by decades of open immigration policies and the arrival of millions of immigrants from across Europe (Hatton & Williamson, 1998). Against this background, I examine how electrification affected social cohesion between native and immigrant manufacturing workers. I study whether the new technology changed the ethnic composition of the workforce and reduced occupational segregation within manufacturing industries. I then assess whether electrification influenced the residential segregation of manufacturing workers and local provision of public services, providing insight into its broader impact on community integration.

2 Historical Background

In the early twentieth century, industrial electrification transformed factory production by replacing centralized steam engines with decentralized electric motors. Under steam power, machines had to be placed close to the central engine to reduce energy loss. Electrification altered this constraint. Once factories could draw affordable and reliable power from external sources, each machine could be equipped with its own motor, allowing production to be arranged around the sequence of operations (Du Boff, 1967; Devine Jr, 1983). As a result, production coalesced around fixed workstations, reducing the need for coordination and movement on the factory floor and giving workers greater task independence (Nye, 2013). The new production system made it easier for employers to hire unskilled and immigrant workers, as tasks required less technical ability, coordination, or shared language. With each worker operating more autonomously, the ethnic background of nearby co-workers mattered less, potentially encouraging more heterogeneous workgroups. As a result, the increased task independence introduced by electrification may have promoted workforce integration within industries, potentially fostering informal interactions and gradual social integration in ethnically mixed communities. Still, greater task independence did not guarantee integration.

Employers might have continued to group workers by ethnicity to avoid tensions or because they believed homogeneous teams were more efficient. As a result, ethnic divisions within the industry could have persisted despite the organizational shift. Whether the technological changes in production brought by electrification actually promoted integration is ultimately an empirical question, which I address in this paper.

3 Data Overview

To measure electrification, I digitize a series of historical maps published by the Edison Electric Institute (EEI, 1962), which trace the expansion of the U.S. high-voltage transmission grid between 1908 and 1946, and maps reporting the locations of major electric power plants, published by the U.S. Department of Commerce (1912) and the U.S. Federal Power Commission (1935). Figure 1 illustrates the expansion of electrification between 1910 and 1940.

By combining these sources, I classify a county as electrified in a given decade if it is connected to the high-voltage grid or is located near a major power plant.[1] I then exploit the staggered expansion of the U.S. electric grid to identify the causal effect of electrification on multiple dimensions of social cohesion between immigrant and native workers.

To examine the employment consequences of electrification, I use individual-level census data aggregated to the industry–county level for the period 1900–1940 (Ruggles et al., 2024). In this paper, "ethnicity" refers to race for U.S.-natives and to country of birth for foreigners, rather than ancestral origin. For example, the "Italian ethnic group" includes people born in Italy who live in the United States, while U.S.-born individuals of Italian descent are classified as U.S.-born Whites. Accordingly, I group workers as U.S.-born Whites, U.S.-born Blacks, and foreign-born individuals ("immigrants") by country of birth.[2]

I use census information on industry and occupation to measure the ethnic characteristics of the labor force in each manufacturing industry, by county and decade. I calculate the share of workers belonging to each ethnic group. Then, I compute an index of ethnic diversity, which measures the probability that two randomly selected workers within an industry belong to different ethnic groups (Alesina et al., 2016). This index captures overall heterogeneity of workforce but not the degree of integration among groups. Two industries could have similar diversity levels, yet differ greatly in how workers from different ethnic backgrounds are distributed across occupations, and ultimately in the degree of ethnic mixing workers actually experience within the industry.

To capture this dimension, I construct an index of ethnic segregation across occupations within each industry, adapted from Alesina and Zhuravskaya (2011). This index measures how unevenly ethnic groups are distributed across occupations relative to their overall share in the industry. It ranges from complete integration, where every occupation mirrors the industry's overall composi-

[1] I exclude the largest urban centers in 1900 from the analysis because they had access to local electric transmission through urban power plants by the late 1890s and early 1900s (Cohn, 2017), while the first available map on power plants dates from 1912.

[2] Combining race for U.S.-born individuals and country of birth for immigrants yields 42 distinct ethnic groups.

tion, to complete segregation, where each occupation is entirely homogeneous. A decrease in ethnic segregation within manufacturing industries implies that occupations, on average, become more ethnically diverse. Panel A of Table 1 shows the summary statistics of the main variables at the industry-county-decade level. Importantly, the indices of ethnic diversity and ethnic segregation are weakly correlated (with a negative correlation coefficient of less than 10%), suggesting that they capture different aspects related to the distribution of ethnic groups within the industry.

4 Empirical Strategy Overview

To assess the causal effect of electrification on the ethnic composition and integration of the labor force in manufacturing industries, I estimate an event-study model, as follows:

$$Y_{qct} = \alpha_{qc} + \phi_{s(c)t} + \delta_{qt} + \sum_{h=-4}^{3} \beta_h \, \mathbb{I}\{K_{ct} = h\} + \mathbf{X}'_{ct}\,\Gamma + \varepsilon_{qct} \tag{1}$$

The unit of observation is a manufacturing industry q in a county c and decade t. The sample includes 51 manufacturing industries, all counties in the continental United States, and covers the period 1900–1940, yielding to 350 thousand unique observations. The treatment variable is an indicator that equals one once a county becomes electrified and its manufacturing industries gain access to the transmission network. The empirical specification includes industry–county fixed effects to control for time-invariant local characteristics—such as geography, natural endowments, or initial industrial structure—that may jointly influence electrification and industrial growth. State–decade fixed effects absorb time-varying state-level shocks and policies, including grid expansion, federal programs, immigration policy changes, and wartime mobilization. Industry–decade fixed effects capture national industry trends and differential rates of electricity adoption across industries. I also include the logarithm of the 1900 county population interacted with decade indicators to account for differences in initial size.

This specification isolates plausibly exogenous variation in the timing of electrification by comparing the same industry across counties that gained access to electricity with those that are not yet electrified. I estimate both the event-study and the corresponding DID models using the imputation-based method of Borusyak et al. (2024), which provides unbiased estimates under staggered treatment adoption. The approach relies on the standard DID assumptions of parallel trends and no anticipation of treatment, for which I provide supporting evidence, and identifies the average treatment effect on the treated (ATT).

5 Employment Consequences of Electrification

My results are consistent with historical accounts suggesting that the reorganization of production brought about by electrification increased the integration of immigrant workers in manufacturing. As highlighted in Table 2, electrification had a positive and statistically significant effect on the share of immigrant workers in manufacturing industries. The group that lost relative representation was U.S.-born Whites, while the effect on U.S.-born Blacks is statistically indistinguishable from zero. The gains were concentrated among immigrants who were culturally and linguistically more distant from the U.S.-born majority—particularly those from Southern and Eastern Europe and from non-English-speaking or non-Protestant countries. These groups faced the greatest communication and cultural barriers and thus benefited most from the reduced need for coordination and communication that electrification afforded. As a result, the ethnic diversity of the workforce in manufacturing industries significantly increased (Figure 2a and Table 3).

Electrification made industries more heterogeneous overall. However, the key question for social cohesion is whether it also promoted integration within industries. I find that electrification significantly reduced ethnic segregation across occupations (Figure 2b and Table 3). This indicates that electrification not only increased overall diversity, but also fostered greater mixing within occupations, expanding opportunities for integration of workers of different ethnic backgrounds within manufacturing industries. This results is driven by occupations directly related to the production process, which become more ethnically diverse after electrification (Table 4). To my knowledge, this provides the first systematic measurement of ethnic segregation across occupations in U.S. manufacturing and offers new evidence on an important but previously unexplored dimension of labor organization.[3] I find considerable variation across industries in the effect of electrification on the integration of ethnically diverse workers (Figure 3). The reduction in ethnic segregation is stronger in industries that were more energy-intensive and operated with larger establishments before electrification (Table 5). These industries likely had greater scope for reorganization and benefited more from the ability to decentralize power.

I perform several tests to assess the validity of the identification strategy and the robustness of the results. A key concern is that the expansion of the grid was not random, as electrification followed geographic and industrial patterns. To address this, I include industry–county, state–decade, and industry–decade fixed effects, which control for time-invariant local characteristics, regional shocks, and national industry trends. The results remain robust when excluding early-electrified areas, hydro-intensive regions, and large urban centers. I also examine potential endogeneity related to manufacturing intensity and county demographics. Electrification is uncorrelated with pre-existing immigrant shares or the ethnic diversity of the county. It also does not affect the overall ethnic composition of the county population, including the shares of foreign-born and Black population, or ethnic diversity. Thus, the estimated industry-level effects are not driven by broader demographic shifts. The results hold when controlling for baseline and time-varying ethnic composition, as well as for manufacturing intensity, and remain stable when excluding counties with extreme initial shares of manufacturing employment.

[3]Margo (1990) calculates a dissimilarity index between Black and White workers in the U.S. South from 1910 to 1940, computed separately by industry and occupation. Tomaskovic-Devey et al. (2006) and Hellerstein and Neumark (2008) examine workplace segregation starting from the 1960s using matched employer–employee data. Xu and Zhang (2022) and Locke (2025) study ethnic–occupational niches in craft and trade occupations during the Age of Mass Migration.

6 Community Consequences of Electrification

Having established that electrification had a causal impact on the integration of ethnically diverse workers within manufacturing industries, I next examine whether it also had effects on social dynamics beyond the workplace. I focus on the community consequences of electrification. A key element of cohesive local communities is the spatial mixing of individuals from different backgrounds, which helps prevent the formation of segregated neighborhoods (Cutler & Glaeser, 1997). Using census data, I calculate an index of residential segregation of manufacturing workers, which captures the degree of ethnic integration across enumeration districts (a proxy for neighborhoods) within each county (Alesina & Zhuravskaya, 2011).

A second key dimension of social cohesion is a community's collective orientation toward the common good, reflected in its willingness to contribute to public goods and services (Schiefer & van der Noll, 2017). Because detailed data on county public finances are unavailable for this period, I proxy local public service provision using the number of workers employed in public service occupations. Using census data, I calculate the number of teachers, doctors, police officers, firefighters, and public administrators per one thousand inhabitants at the county level. Prior research shows that areas with larger immigrant populations tend to provide fewer public goods, both historically and today (Tabellini, 2020; Alesina et al., 2023). This pattern reflects the broader challenge of achieving social cohesion in ethnically diverse societies (Alesina et al., 1999; Alesina & La Ferrara, 2000). Building on my earlier results showing that electrification increased the integration of diverse manufacturing workers, I examine whether it also weakened the negative relationship between immigrant presence and the provision of local public services, particularly in counties with high manufacturing intensity.

To estimate the effect of electrification on the residential segregation of manufacturing workers, I use a difference-in-differences model estimated at the county c decade t level—covering all counties in the continental United States in the period 1900-1940—as follows[4]:

$$Y_{ct} = \alpha_c + \phi_{s(c)t} + \beta_t \, \mathbb{I}\{t \geq \mathit{Electrified}_c\} + \mathbf{X}'_{ct}\,\Gamma + \varepsilon_{ct} \tag{2}$$

To assess its effect on the provision of local public services, I estimate an OLS regression with the county's immigrant share, a post-electrification indicator, and their interaction as key explanatory variables.

$$\begin{aligned} Y_{ct} = \alpha_c + \phi_{s(c)t} + \beta_1 \, \mathbb{I}\{t \geq \mathit{Electrified}_c\} + \beta_2 \, \mathit{Immigrant\ Share}_{ct} \\ + \beta_3 \, \mathit{Immigrant\ Share}_{ct} \times \mathbb{I}\{t \geq \mathit{Electrified}_c\} + \mathbf{X}'_{ct}\,\Gamma + \varepsilon_{ct} \end{aligned} \tag{3}$$

Both models include county fixed effects, state-by-decade fixed effects, and interactions of decade indicators with the 1900 county population and manufacturing employment share. These controls account for baseline differences in population size and manufacturing intensity, as well as for time-

[4]This model is also estimated using the imputation-based method of Borusyak et al. (2024). Panel B of Table 1 shows the summary statistics of the main variables at the industry-county-decade level.

invariant county characteristics and state-specific time trends.

In Tables 6 and 7, I show that residential segregation among manufacturing workers significantly declined in electrified counties compared to non-electrified ones. This suggests that electrification was associated with greater integration not only within manufacturing industries but also within the neighborhoods where workers lived. This result is driven by counties with a manufacturing sector largely intensive in energy at baseline, and it holds even when taking into account second-generation immigrants.

Regarding local public services, in Table 8, I find a negative and statistically significant relationship between the immigrant share and public service employment, consistent with previous evidence. The interaction between immigrant share and electrification is positive and statistically significant, but only in counties with high baseline manufacturing intensity. These findings suggest that electrification partially mitigated the negative association between immigrant presence and local public service provision, consistent with its furnishing greater social cohesion and improving the integration of immigrant manufacturing workers into local communities.

Finally, I examine whether electrification affected the cultural assimilation of immigrant manufacturing workers. A priori, it is unclear how immigrants will adjust their cultural identity as they become more economically and socially integrated. On one hand, immigrants experiencing reduced social and economic distance from natives may be more likely to assimilate culturally (Fouka et al., 2022; Abramitzky et al., 2024). On the other hand, assimilation may be a response to discrimination, so that well-integrated immigrants may feel less pressure to signal assimilation and instead choose to preserve their ethnic identity (Fouka, 2019, 2020). Accordingly, results on assimilation are mixed (Table 9). I find a modest increase in intermarriage between immigrants and natives in electrified counties, consistent with greater social integration. However, I find no systematic change in the naming patterns of children born to immigrant parents. Overall results suggest that while electrification may have fostered closer social ties, it did not necessarily lead to broader changes in cultural assimilation.

7 Conclusions

Taken together, my results show that by removing barriers that keep workers segregated on the job, technological change in production can promote integration at work and in the community, strengthening social cohesion within local communities.

This paper builds on an established literature showing that radical technological change often requires a deep reorganization of production and the adoption of complementary innovations to realize productivity gains. These dynamics have been documented in the diffusion of the steam engine and the rise of the factory system (Sokoloff, 1984; Mokyr, 2001; Juhász et al., 2024), electricity (Du Boff, 1967; Devine Jr, 1983; David, 1990; Atkeson & Kehoe, 2007), and modern information and communication technologies (Brynjolfsson & Hitt, 2000; Syverson, 2011; Brynjolfsson et al., 2025).[5] Building on this insight, I provide empirical evidence that changes in production processes can also influence how workers are integrated in the workplace, with broader implications for social cohesion.[6]

This contribution advances the emerging literature that examines how technological change in the way industries operate and produce can shape social dynamics. Acemoglu and Wolitzky (2025) develop a model linking workplace relations and community interactions, showing that technologies which increase workplace monitoring can weaken informal ties and reduce community cooperation, ultimately eroding local social capital. In contrast, my paper provides empirical evidence that production technologies that reduce barriers between diverse workers can promote integration. Most empirical work in this area has focused on gender, showing that electrification and automation increased female labor participation and improved women's economic and social status (Cortés et al., 2024; Feigenbaum & Gross, 2024; Vidart, 2024; Forslund et al., 2025; Vidart, 2025; Ager et al., 2026). I extend this line of research by examining the effects of technological change on immigrant workers, another historically marginalized group.

While this paper examines the effects of electrification in manufacturing on the integration of ethnically diverse workers, the underlying mechanisms are not unique to this context. For example, the adoption of containerized shipping standardized handling tasks and reduced reliance on informal ethnic labor networks that had long dominated port work (Levinson, 2016). Similarly, the spread of office mechanization—and later digital communication technologies—standardized and codified tasks, formalized communication within offices, and routinized workflows through written documentation and formal systems, reducing the importance of shared language, cultural background, and social proximity (Chandler Jr & Cortada, 2000; Beniger, 2009).

Ultimately, understanding the specific features of technological change that promote integration and those that deepen existing social divisions remains an important question for future research. Identifying these mechanisms can help explain when and how technological progress contributes not only to economic growth, but also to more cohesive and inclusive societies.

[5] Radical technological changes that affect a wide range of sectors and industries (e.g., steam, electricity, internal combustion engine, information technologies), and that can transform both household life and firm organization, are referred to as "general-purpose technologies" (David, 1990; Bresnahan & Trajtenberg, 1995; Helpman, 1998; David & Wright, 2003; Jovanovic & Rousseau, 2005; Mokyr, 2005).

[6] A large empirical literature studies the effects of technological change on workers and labor markets, focusing on wage inequality, job polarization, and the skill composition of the labor force (Katz & Murphy, 1992; Goldin & Katz, 1998; Caroli & Van Reenen, 2001; Card & DiNardo, 2002; Autor et al., 2003, 2006; Acemoglu & Autor, 2011; Autor & Dorn, 2013; Acemoglu & Restrepo, 2019, 2020; Jaimovich & Siu, 2020).

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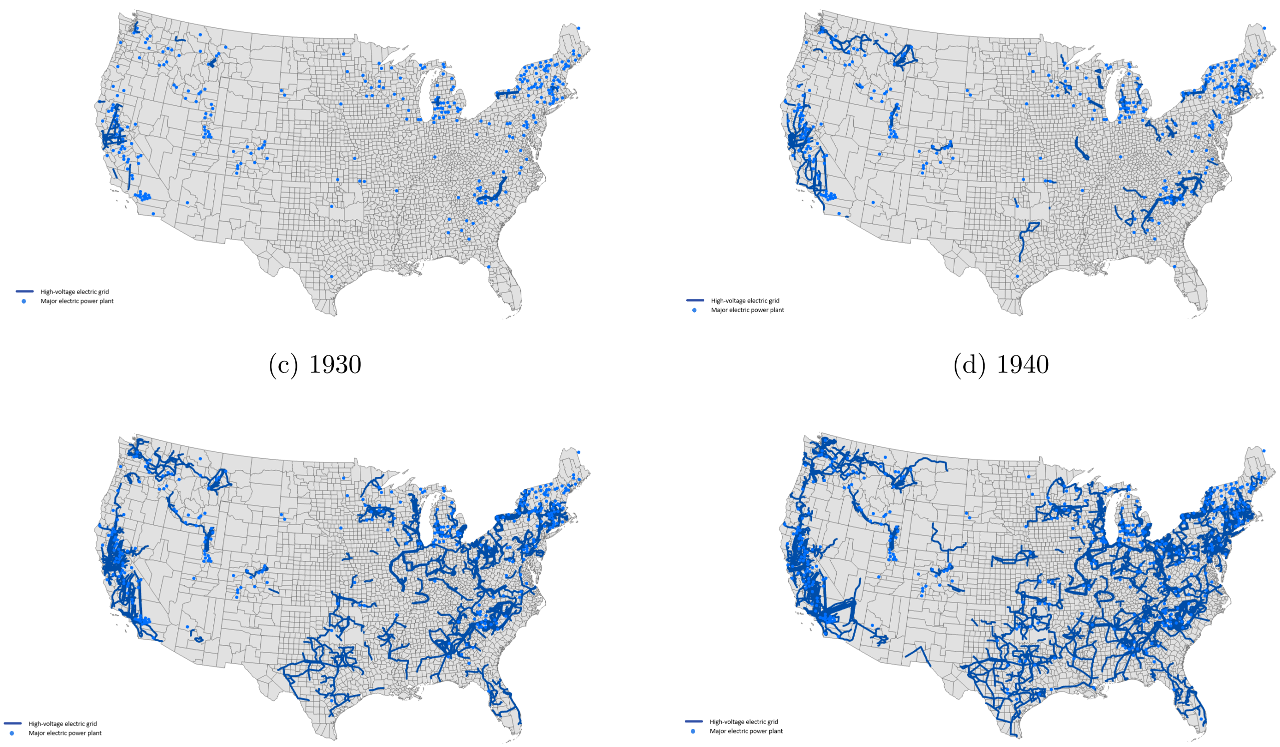
Figures

Figure 1: Electrification expansion in the United States, 1910–1940

(a) 1910 (b) 1920

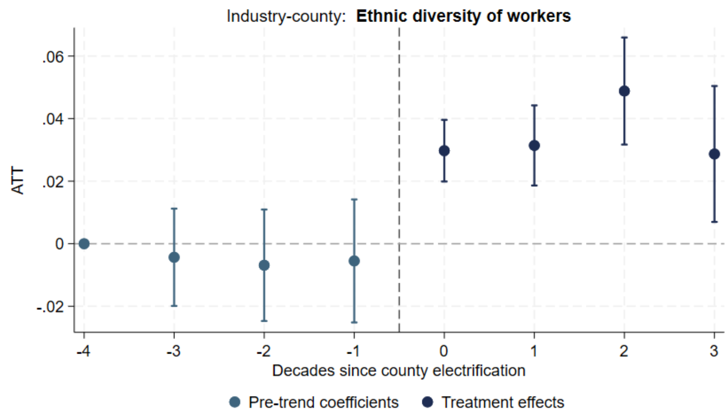
(c) 1930 (d) 1940



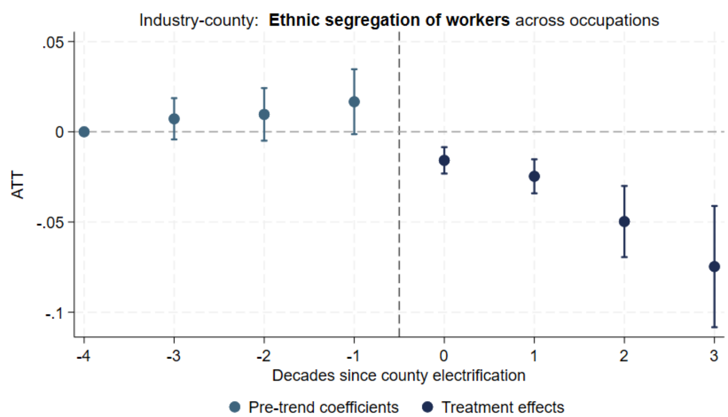
Note: This figure illustrates the decennial expansion of electrification between 1910 and 1940. The dark-blue lines represent the high-voltage electric grid, while the light-blue dots indicate the location of a major electric power plant. For 1910, Figure 1a shows the 1908 electric grid map and the 1912 power plant data. For 1920, Figure 1b shows the 1918 electric grid map and the 1912 power plants. For 1930, Figure 1c shows the 1928 electric grid map and the 1912 power plants. For 1940, Figure 1d shows the 1940 electric grid map, along with the 1935 and 1912 power plants. The maps of the high-voltage grid are digitized from the Edison Electrical Institute (1962); the map of the 1912 power plants is digitized from the U.S. Department of Commerce (1912); the map of the 1935 power plants is digitized from the U.S. Federal Power Commission (1935). A county c is considered as “treated” in decade t if at least one of the following conditions is met: (i) the county lies within a 50 km (ca. 30 miles) radius of a central power station, or (ii) the county is intersected by a 5 km (ca. 3 miles) buffer around a high-voltage transmission line. Appendix Figure ?? shows the set of electrified counties by decade.

Figure 2: Event study results: Electrification and ethnic integration of the labor force in manufacturing industries

(a) Ethnic diversity of workers within manufacturing industry

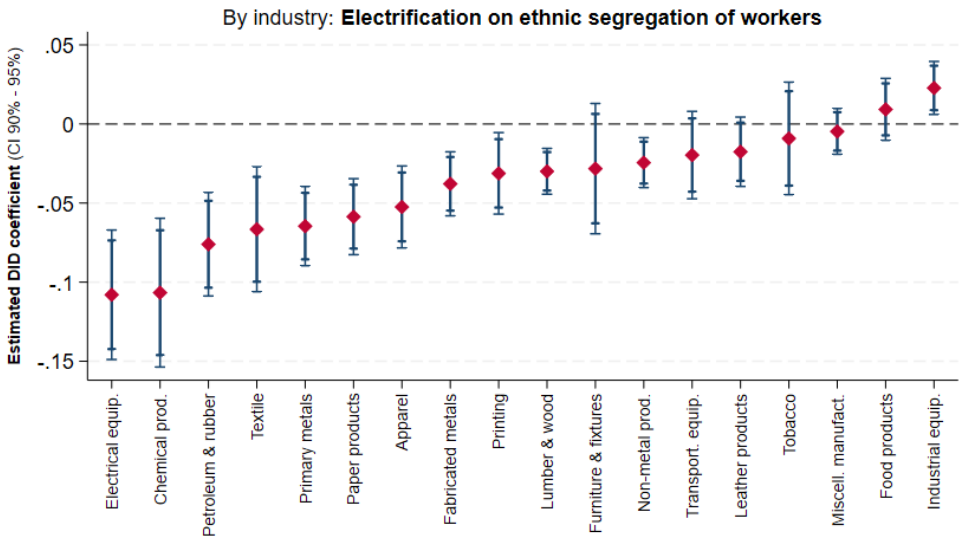


(b) Ethnic segregation of workers across occupations within manufacturing industry



Note: This figure shows the event study coefficients estimated with the imputation method by Borusyak et al. (2024). Figure 2a shows the results for the ethnic diversity of workers within the manufacturing industry (from 0 = "complete homogeneity" to 1 = "complete heterogeneity"). Figure 2b reports the results for the ethnic segregation of workers across occupations within the manufacturing industry (from 0 ="no segregation" to 1 = "complete segregation"). The unit of analysis is a manufacturing industry q in county c and decade t. Counties are consistent over time, fixed at the 1900 borders. The y-axis reports the estimated coefficient and the 95% confidence interval of the difference between treated and control units (i.e., the average treatment effect on the treated, ATT). The horizontal dashed line indicates 0, i.e., no difference between the treated and control units. The vertical, dashed line indicates the occurrence of treatment (i.e., electrification). A county c "treated" in decade t if it is electrified. All industries located in an electrified county are treated. The x-axis shows the number of decades since treatment (event study periods): electrification happens in period 0, negative values indicate pre-treatment and positive values indicate post-treatment periods. The estimation method sets the estimated coefficient of the pre-treatment period farthest from the treatment to 0. All estimation models include: (i) industry $\times$ county FEs, (ii) state $\times$ decade FEs, (iii) industry $\times$ decade FEs, and (iv) the county population in 1900 $\times$ decade dummies as control. The sample excludes counties with population levels in the year 1900 above the 99th percentile of the distribution. Estimates are weighted by the industry share of employment. Standard errors are clustered at the county level. Estimated coefficients are reported in Appendix Table **??** and the outcomes' trends in the data is shown in Appendix Figure **??**.

Figure 3: Heterogenity by industry: Electrification and ethnic integration of the labor force in manufacturing industries



Note: This figure shows the effect of electrification on the ethnic segregation of workers across occupations within industry, separated by 2-digit SIC industries. The unit of analysis is a manufacturing industry q in county c and decade t. Each manufacturing industry q belongs to a broader industrial category defined by 2-digit SIC codes. Counties are consistent over time, fixed at the 1900 borders. Each reported coefficient is obtained by the DID estimation performed with the imputation method by Borusyak et al. (2024), allowing for heterogeneity across 2-digit SIC industries. The x-axis specifies the industry. The y-axis reports the estimated DID coefficient and the 90% and 95% confidence interval of the difference between treated and control units (i.e., the average treatment effect on the treated, ATT), corresponding to the industry reported on the x-axis. A county c "treated" in decade t if it is electrified. All industries located in an electrified county are treated. The estimation model includes: (i) industry $\times$ county FEs, (ii) state $\times$ decade FEs, (iii) industry $\times$ decade FEs, and (iv) the county population in 1900 $\times$ decade dummies as control. The sample excludes counties with population levels in the year 1900 above the 99th percentile of the distribution. Estimates are weighted by the industry share of employment. Standard errors are clustered at the county level.

Tables

Table 1: Summary Statistics

	Num.	Mean	St. Dev.	Pctl. 1	Pctl. 5	Pctl. 95	Pctl. 99
Panel A: Industry-county-decade							
$\textit{Employment Number}_{qct}$	356,442	87.96	907.37	0.017	1	256	1,394
$\textit{Employment Share}_{qct}$	356,442	0.004	0.014	0.000	0.0001	0.014	0.055
$\textit{Immigrant Share}_{qct}$	356,442	0.104	0.210	0	0	0.529	1
$\textit{Native White Share}_{qct}$	356,442	0.812	0.276	0	0.027	1	1
$\textit{Native Black Share}_{qct}$	356,442	0.084	0.216	0	0	0.625	1
$\textit{Ethnic Diversity}_{qct}$	309,020	0.147	0.214	0	0	0.597	0.740
$\textit{Ethnic Segregation}_{qct}$	178,453	0.202	0.228	0	0	0.680	0.905
Panel B: County-decade							
$\textit{Total Population ('000)}_{ct}$	14,097	37.470	122.51	1.364	3.692	96.246	388.32
$\textit{Immigrant Popul. Share}_{ct}$	14,097	0.068	0.085	0.0001	0.0005	0.245	0.353
$\textit{Immigrant Groups Number}_{ct}$	14,097	27.222	9.884	1	3	36	40
$\textit{Native Black Share}_{ct}$	14,097	0.120	0.196	0	0	0.582	0.767
$\textit{Manufact. Workers Number}_{ct}$	14,097	2,224.1	12,258.5	3	16	7,675	35,763
$\textit{Manufact. Sector Share}_{ct}$	14,097	0.094	0.100	0.003	0.008	0.312	0.440
$\textit{Manufact. Industries Number}_{ct}$	14,097	25.285	13.225	2	6	49	68
$\textit{Residential Segregation}_{ct}$	11,766	0.096	0.126	0.006	0.014	0.296	0.612
$\textit{Foreignness Children Names}_{ct}$	8,614	45.394	12.698	7.195	22.545	64.723	77.118
$\textit{Native-Foreign Intermarr. Rate}_{ct}$	13,768	0.060	0.119	0	0	0.301	0.500
$\textit{Num. Public Service Occ. (/1,000)}_{ct}$	14,097	9.655	3.760	2.865	4.109	16.129	20.219
$\textit{Num. Teachers (/1,000)}_{ct}$	14,097	7.615	3.202	1.852	2.879	13.201	16.611
$\textit{Num. Doctors (/1,000)}_{ct}$	14,097	1.041	0.530	0.178	0.386	1.973	2.521
$\textit{Num. Policemen (/1,000)}_{ct}$	14,097	0.438	0.441	0	0	1.241	2.047
$\textit{Num. Firefighters (/1,000)}_{ct}$	14,097	0.104	0.225	0	0	0.610	1.034
$\textit{Num. Public Admin. (/1,000)}_{ct}$	14,097	0.457	0.826	0	0	1.550	3.110

Note: This table shows the summary statistics of the key variables at the industry-county-decade level (Panel A) and at the county-decade level (Panel B).

Table 2: DID results: Electrification and ethnic composition of the labor force in manufacturing industries

	Industry-county-decade level analysis		
	Share Immigrant Workers (1)	*Share Native White Workers* (2)	*Share Native Black Workers* (3)
Electrified	0.016***	-0.016***	-0.0002
	(0.005)	(0.006)	(0.003)
Observation N	276,245	276,245	276,245
Cluster N	2,799	2,799	2,799
Outcome Mean$_{1900}$	0.188	0.742	0.070
Outcome Mean$_{\text{Non-treated}}$	0.110	0.797	0.093
Industry × County FE	✓	✓	✓
State × Decade FE	✓	✓	✓
Industry × Decade FE	✓	✓	✓
County Population$_{1900}$ × $\mathbb{I}_t$	✓	✓	✓
Clustered SE: County$_{1900}$	✓	✓	✓
Pre-trend Test: F-stat	0.149	0.679	1.282
$\beta_{h<0} = 0$ [p-value]	[0.930]	[0.565]	[0.279]

Note: This table reports the difference-in-differences (DID) coefficients estimated with the imputation method by Borusyak et al. (2024). The estimated coefficient is the difference between treated and control units in the post-treatment period (i.e., the average treatment effect on the treated, or ATT). The unit of analysis is a manufacturing industry q in a county c and decade t. Counties are consistent over time, fixed at the 1900 borders. The dependent variable is reported at the top of the table: in column (1), the share of immigrant (foreign-born) workers in the industry; in column (2), the share of White U.S.-born workers in the industry; and in column (3), the share of Black U.S.-born workers in the industry. The variable *Electrified* indicates the treatment: a county c is considered as "treated" in decade t if it is electrified. Once a county gets treated, it remains treated for the following periods. All manufacturing industries located in an electrified county are treated. All estimation models include: (i) industry × county FEs, (ii) state × decade FEs, (iii) industry × decade FEs, and (iv) the county population in 1900 × decade dummies as control. The sample excludes counties with population levels in the year 1900 above the 99th percentile of the distribution (29 counties that host the largest U.S. cities, which are considered as "always treated"). Estimates are weighted by the industry share of employment in the county. Standard errors are clustered at the county level and are reported in parentheses below the coefficients. The table reports the F-statistics and the corresponding p-value (in square brackets) of the direct test for the hypothesis that all pre-treatment coefficients are jointly $= 0$ ($\beta_{h<0} = 0$, where $h = 0$ indicates the period in which treatment starts). Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: DID results: Electrification and ethnic integration of the labor force in manufacturing industries

	Industry-county-decade level analysis					
	Ethnic Diversity		*Ethnic Segregation*			
	(1)	(2)	(3)	(4)	(5)	(6)
Electrified	0.034***	0.021***	-0.035***	-0.035***	-0.026***	-0.026***
	(0.006)	(0.004)	(0.006)	(0.006)	(0.006)	(0.006)
Observation N	235,062	235,062	122,264	122,264	89,246	89,246
Cluster N	2,799	2,799	2,710	2,710	2,554	2,554
Outcome Mean_{1900}	0.201	0.201	0.114	0.114	0.114	0.114
Outcome $\text{Mean}_{\text{Non-treated}}$	0.132	0.132	0.184	0.184	0.184	0.184
Industry × County FE	✓	✓	✓	✓	✓	✓
State × Decade FE	✓	✓	✓	✓	✓	✓
Industry × Decade FE	✓	✓	✓	✓	✓	✓
County $\text{Population}_{1900} \times \mathbb{I}_t$	✓	✓	✓	✓	✓	✓
Clustered SE: County_{1900}	✓	✓	✓	✓	✓	✓
Add. Control: *Share White Natives*	✗	✓	✗	✓	✗	✓
Add. Control: *Ethnic Diversity*			✗	✗	✓	✓
Pre-trend Test: F-stat	0.239	0.701	1.300	1.327	1.076	0.993
$\beta_{h<0} = 0$ [p-value]	[0.869]	[0.551]	[0.273]	[0.327]	[0.358]	[0.395]

Note: This table reports the difference-in-differences (DID) coefficients estimated with the imputation method by Borusyak et al. (2024). The estimated coefficient is the difference between treated and control units in the post-treatment period (i.e., the average treatment effect on the treated, or ATT). The unit of analysis is a manufacturing industry q in a county c and decade t. Counties are consistent over time, fixed at the 1900 borders. The dependent variable is reported at the top of the table: in columns (1)-(2), the index of ethnic diversity of workers within the industry (from 0 = "complete homogeneity" to 1 = "complete heterogeneity"); and in columns (3)-(6), the index of ethnic segregation of workers across occupations within the industry (from 0 = "no segregation" and 1 = "complete segregation"). The variable *Electrified* indicates the treatment: a county c is considered as "treated" in decade t if it is electrified. Once a county gets treated, it remains treated for the following periods. All manufacturing industries located in an electrified county are treated. All estimation models include: (i) industry × county FEs, (ii) state × decade FEs, (iii) industry × decade FEs, and (iv) the county population in 1900 × decade dummies as control. Columns (2) and (4)-(6) show the results for the same model as in column (1) and (3), respectively, with the addition of industry-county-decade controls, as specified in the table. The sample excludes counties with population levels in the year 1900 above the 99th percentile of the distribution (29 counties that host the largest U.S. cities, which are considered as "always treated"). Estimates are weighted by the industry share of employment in the county. Standard errors are clustered at the county level and are reported in parentheses below the coefficients. The table reports the F-statistics and the corresponding p-value (in square brackets) of the direct test for the hypothesis that all pre-treatment coefficients are jointly $= 0$ ($\beta_{h<0} = 0$, where $h = 0$ indicates the period in which treatment starts). Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Heterogeneity by occupation characteristics within the industry – DID Results: Electrification and ethnic diversity of the labor force in manufacturing industries

	Industry-county-decade level analysis			
	Ethnic Diversity of Workers			
	In Production-Related Occupations		In Production-Unrelated Occupations	
	(1)	(2)	(3)	(4)
Electrified	0.035***	0.015***	-0.002*	-0.004***
	(0.005)	(0.002)	(0.001)	(0.001)
Observation N	259,616	219,319	128,921	105,370
Cluster N	2,799	2,799	2,768	2,747
Outcome Mean_{1900}	0.175	0.175	0.016	0.016
Outcome $\text{Mean}_{\text{Non-treat.}}$	0.115	0.115	0.012	0.012
Industry × County FE	✓	✓	✓	✓
State × Decade FE	✓	✓	✓	✓
Industry × Decade FE	✓	✓	✓	✓
County $\text{Popul.}_{1900} \times \mathbb{I}_t$	✓	✓	✓	✓
Clust. SE: County_{1900}	✓	✓	✓	✓
Add. Cntr: *Industry Ethnic Diversity*	✗	✓	✗	✓
Pre-trend Test: F-stat	0.317	1.749	0.917	1.277
$\beta_{h<0} = 0$ [p-value]	[0.813]	[0.155]	[0.432]	[0.281]

Note: This table reports the difference-in-differences (DID) coefficients estimated with the imputation method by Borusyak et al. (2024). The estimated coefficient is the difference between treated and control units in the post-treatment period (i.e., the average treatment effect on the treated, or ATT). The unit of analysis is a manufacturing industry q in a county c and decade t. Counties are consistent over time, fixed at the 1900 borders. The dependent variable is the index of ethnic diversity of workers within **occupation categories**, within the industry (from 0 = "complete homogeneity" to 1 = "complete heterogeneity"). Occupations are divided between *production-related* in columns (1)-(2) and *production-unrelated* in columns (3)-(4). The variable *Electrified* indicates the treatment: a county c is considered as "treated" in decade t if it is electrified. Once a county gets treated, it remains treated for the following periods. All manufacturing industries located in an electrified county are treated. All estimation models include: (i) industry × county FEs, (ii) state × decade FEs, (iii) industry × decade FEs, and (iv) the county population in 1900 × decade dummies as control. The models in columns (2) and (4) also include the ethnic diversity calculated at the industry-level as additional control. The sample excludes counties with population levels in the year 1900 above the 99th percentile of the distribution (29 counties that host the largest U.S. cities, which are considered as "always treated"). Estimates are weighted by the industry share of employment in the county. Standard errors are clustered at the county level and are reported in parentheses below the coefficients. The table reports the F-statistics and the corresponding p-value (in square brackets) of the direct test for the hypothesis that all pre-treatment coefficients are jointly = 0 ($\beta_{h<0} = 0$, where $h = 0$ indicates the period in which treatment starts). Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Heterogeneity by industry characteristics – DID Results: Electrification and ethnic integration of the labor force in manufacturing industries

	Industry-county-decade level analysis							
	Ethnic Segregation of Workers							
	Energy Use Intensity						Scope for Reorganization	
	Energy Expense$_{1900}$ $\left[\frac{\text{Fuel\&Energy Expend.}}{\text{Value Production}}\right]$		Energy Use$_{1930}$ $\left[\frac{\text{Tot. Horsepower}}{\text{Value Production}}\right]$		Electricity Use$_{1963}$ $\left[\frac{\text{Ind. Electricity Cons.}}{\text{Manuf. Electr. Cons.}}\right]$		Establishment Size$_{1900}$ $\left[\frac{\text{Tot. Workers}}{\text{Tot. Establishm.}}\right]$	
	High	Low	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Electrified	-0.050***	-0.021***	-0.039***	-0.024***	-0.041***	-0.027***	-0.043***	-0.015**
	(0.009)	(0.006)	(0.007)	(0.008)	(0.008)	(0.006)	(0.007)	(0.007)
Observation N	48,577	73,687	64,107	58,157	71,579	50,685	60,836	61,428
Cluster N	2,518	2,679	2,623	2,637	2,588	2,660	2,625	2,628
Outcome Mean$_{1900}$	0.129	0.105	0.119	0.108	0.112	0.116	0.125	0.104
Outcome Mean$_{\text{Non-treat.}}$	0.198	0.174	0.172	0.196	0.198	0.164	0.185	0.183
Industry × County FE	✓	✓	✓	✓	✓	✓	✓	✓
State × Decade FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry × Decade FE	✓	✓	✓	✓	✓	✓	✓	✓
County Popul.$_{1900}$ × $\mathbb{I}_t$	✓	✓	✓	✓	✓	✓	✓	✓
Clust. SE: County$_{1900}$	✓	✓	✓	✓	✓	✓	✓	✓
Pre-trend Test: F-stat	1.300	1.300	1.300	1.300	1.300	1.300	1.300	1.300
$\beta_{h<0} = 0$ [p-value]	[0.273]	[0.273]	[0.273]	[0.273]	[0.273]	[0.273]	[0.273]	[0.273]

Note: This table reports the difference-in-differences (DID) coefficients estimated with the imputation method by Borusyak et al. (2024). The estimated coefficient is the difference between treated and control units in the post-treatment period (i.e., the average treatment effect on the treated, or ATT). The unit of analysis is a manufacturing industry q in a county c and decade t. Counties are consistent over time, fixed at the 1900 borders. The dependent variable is the index of ethnic segregation of workers across occupations within the industry (from 0 = "no segregation" and 1 = "complete segregation"). The variable *Electrified* indicates the treatment: a county c is considered as "treated" in decade t if it is electrified. Once a county gets treated, it remains treated for the following periods. All manufacturing industries located in an electrified county are treated. Results are reported by **industry characteristics**: fuel and energy expenses over value of production in 1900 in columns (1)-(2) (from census of manufacturers); total horsepower per value of production in 1930 in columns (3)-(4) (from census of manufacturers); share of electricity use in manufacturing in 1963 in columns (5)-(6) (from input-output tables); average establishment size (number of workers) in 1900 in columns (7)-(8) (from census of manufacturers). High/low is defined as above/below the median, at the national and industry level in the year of reference. All estimation models include: (i) industry × county FEs, (ii) state × decade FEs, (iii) industry × decade FEs, and (iv) the county population in 1900 × decade dummies as control. The sample excludes counties with population levels in the year 1900 above the 99th percentile of the distribution (29 counties that host the largest U.S. cities, which are considered as "always treated"). Estimates are weighted by the industry share of employment in the county. Standard errors are clustered at the county level and are reported in parentheses below the coefficients. The table reports the F-statistics and the corresponding p-value (in square brackets) of the direct test for the hypothesis that all pre-treatment coefficients are jointly = 0 ($\beta_{h<0} = 0$, where $h = 0$ indicates the period in which treatment starts). Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: DID results: Electrification and residential segregation of the manufacturing labor force

	County-decade level analysis					
	Residential Segregation of Manufacturing Workers					
	Baseline Definition of Ethnicity			Incl. Second Generat. Immigr.		
	(1)	(2)	(3)	(4)	(5)	(6)
Electrified	-0.010***	-0.012***	-0.010***	-0.008**	-0.009***	-0.008**
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Observation N	11,036	11,036	11,036	11,036	11,036	11,036
Cluster N	2,574	2,574	2,574	2,574	2,574	2,574
Outcome Mean_{1900}	0.090	0.090	0.090	0.091	0.091	0.091
Outcome $\text{Mean}_{\text{Non-treated}}$	0.107	0.107	0.107	0.109	0.109	0.109
County FE	✓	✓	✓	✓	✓	✓
State × Decade FE	✓	✓	✓	✓	✓	✓
County $\text{Population}_{1900} \times \mathbb{I}_t$	✓	✓	✓	✓	✓	✓
Manufacture $\text{Share}_{1900} \times \mathbb{I}_t$	✓	✓	✓	✓	✓	✓
Clustered SE: County_{1900}	✓	✓	✓	✓	✓	✓
Add. Cntr: *Share White Natives*	✗	✓	✗	✗	✓	✗
Add. Cntr: *Share 2nd-Gener. Immigr.*				✗	✓	✗
Add. Cntr: *Ethnic Diversity*	✗	✗	✓	✗	✗	✓
Pre-trend Test: F-stat	0.588	0.524	0.579	0.331	0.218	0.348
$\beta_{h<0} = 0$ [p-value]	[0.623]	[0.666]	[0.629]	[0.803]	[0.884]	[0.791]

Note: This table reports the difference-in-differences (DID) coefficients estimated with the imputation method by Borusyak et al. (2024). The estimated coefficient is the difference between treated and control units in the post-treatment period (i.e., the average treatment effect on the treated, or ATT). The unit of analysis is a county c in a decade t. Counties are consistent over time, fixed at the 1900 borders. The dependent variable is the index of residential segregation of manufacturing workers across enumeration districts within the county (from 0 = "no segregation" and 1 = "complete segregation"). In columns (1)–(3), residential segregation is computed using the baseline definition of ethnic groups: U.S.-born Whites, U.S.-born Blacks, and foreign-born individuals classified by their country of birth. In columns (4)–(6), the measure is recalculated to include second-generation immigrants—U.S.-born individuals with foreign-born parents—grouped together with the foreign-born. Second-generation individuals are assigned to an ethnic group based on the father's country of birth. In this case, White and Black U.S.-natives are defined as individuals born in the U.S. to U.S.-born parents. The variable *Electrified* indicates the treatment: a county c is considered as "treated" in decade t if it is electrified. Once a county gets treated, it remains treated for the following periods. All estimation models include: (i) county FEs, (ii) state × decade FEs, (iii) the county population in 1900 × decade dummies as control, and (iv) the county share of manufacturing employment in 1900 × decade dummies as control. Columns (2) and (3) show the results of the same model as in column (1), additionally controlling for the county share of White U.S.-native and the county ethnic diversity, respectively. Columns (5) and (6) show the results of the same model as in column (4), additionally controlling for the county share of White U.S.-native plus share of U.S.-native with foreign-born parents and the county ethnic diversity, respectively. The sample excludes counties with population levels in the year 1900 above the 99th percentile of the distribution (29 counties that host the largest U.S. cities, which are considered as "always treated"). Estimates are weighted by the manufacturing share of employment in the county. Standard errors are clustered at the county level and are reported in parentheses below the coefficients. The table reports the F-statistics and the corresponding p-value (in square brackets) of the direct test for the hypothesis that all pre-treatment coefficients are jointly = 0 ($\beta_{h<0} = 0$, where $h = 0$ indicates the period in which treatment starts). Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Heterogeneity by county manufacturing characteristics – DID results: Electrification and residential segregation of the manufacturing labor force

	County-decade level analysis			
	Residential Segregation of Manufacturing Workers			
	Baseline Definition of Ethnicity		Incl. Second Generat. Immigr.	
	Manuf. Energy Intensity$_{1900}$		Manuf. Energy Intensity$_{1900}$	
	High	Low	High	Low
	(1)	(2)	(3)	(4)
Electrified	-0.014***	-0.004	-0.012***	-0.002
	(0.004)	(0.005)	(0.004)	(0.005)
Observation N	5,865	5,171	5,865	5,171
Cluster N	1,319	1,255	1,319	1,255
Outcome Mean$_{1900}$	0.090	0.091	0.089	0.093
Outcome Mean$_{\text{Non-treated}}$	0.110	0.103	0.114	0.102
County FE	✓	✓	✓	✓
State × Decade FE	✓	✓	✓	✓
County Population$_{1900}$ $\times \mathbb{I}_t$	✓	✓	✓	✓
Manufacture Share$_{1900}$ $\times \mathbb{I}_t$	✓	✓	✓	✓
Clustered SE: County$_{1900}$	✓	✓	✓	✓
Pre-trend Test: F-stat	0.588	0.588	0.331	0.331
$\beta_{h<0} = 0$ [p-value]	[0.623]	[0.623]	[0.803]	[0.803]

Note: This table reports the difference-in-differences (DID) coefficients estimated with the imputation method by Borusyak et al. (2024). The estimated coefficient is the difference between treated and control units in the post-treatment period (i.e., the average treatment effect on the treated, or ATT). The unit of analysis is a county c in a decade t. Counties are consistent over time, fixed at the 1900 borders. The dependent variable is the index of residential segregation of manufacturing workers across enumeration districts within the county (from 0 = "no segregation" and 1 = "complete segregation"). In columns (1)–(3), residential segregation is computed using the baseline definition of ethnic groups: U.S.-born Whites, U.S.-born Blacks, and foreign-born individuals classified by their country of birth. In columns (4)–(6), the measure is recalculated to include second-generation immigrants—U.S.-born individuals with foreign-born parents—grouped together with the foreign-born. Second-generation individuals are assigned to an ethnic group based on the father's country of birth. In this case, White and Black U.S.-natives are defined as individuals born in the U.S. to U.S.-born parents. The variable *Electrified* indicates the treatment: a county c is considered as "treated" in decade t if it is electrified. Once a county gets treated, it remains treated for the following periods. Results are reported by a **characteristic of the manufacturing sector at the county level**: the average energy intensity of the manufacturing industries in the county in 1900, calculated as the ratio of average energy expenses to the value of production at the industry level (from the census of manufacturers). High/low is defined as above/below the median, considering all counties in the year of reference. All estimation models include: (i) county FEs, (ii) state × decade FEs, (iii) the county population in 1900 × decade dummies as control, and (iv) the county share of manufacturing employment in 1900 × decade dummies as control. The sample excludes counties with population levels in the year 1900 above the 99th percentile of the distribution (29 counties that host the largest U.S. cities, which are considered as "always treated"). Estimates are weighted by the manufacturing share of employment in the county. Standard errors are clustered at the county level and are reported in parentheses below the coefficients. The table reports the F-statistics and the corresponding p-value (in square brackets) of the direct test for the hypothesis that all pre-treatment coefficients are jointly = 0 ($\beta_{h<0} = 0$, where $h = 0$ indicates the period in which treatment starts). Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: OLS results: Electrification and provision of local public services

	County-decade level analysis				
	Workers in All Occupations Related to Public Service Provision				
		Share Cnty. Empl. Manufacturing$_{1900}$		Share Cnty. Empl. High-Energy Manuf.$_{1900}$	
	All Counties	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)
Electrified	-0.213***	-0.298***	0.080	-0.248***	-0.120
	(0.071)	(0.090)	(0.105)	(0.093)	(0.104)
Imm. Share	-9.987***	-12.061***	-1.580	-11.784***	-3.488
	(1.198)	(1.373)	(1.710)	(1.305)	(2.217)
Imm. Share × *Electr.*	1.845***	2.709***	-3.106**	2.368***	1.471
	(0.630)	(0.686)	(1.389)	(0.733)	(2.336)
Observation N	13,797	6,825	6,962	6,845	6,942
Cluster N	2,763	1,366	1,395	1,370	1,391
Outcome Mean$_{1900}$	7.766	7.990	7.546	8.774	6.779
Outcome Mean$_{\text{Non-treated}}$	9.033	8.636	9.311	9.855	8.394
County FE	✓	✓	✓	✓	✓
State × Decade FE	✓	✓	✓	✓	✓
County Popul.$_{1900}$ × $\mathbb{I}_t$	✓	✓	✓	✓	✓
Manuf. Share$_{1900}$ × $\mathbb{I}_t$	✓	✓	✓	✓	✓
Clust. SE: County$_{1900}$	✓	✓	✓	✓	✓

Note: This table reports the OLS coefficients of the regression model with an interaction term between the county share of immigrant population (*Perc. Immigrant*) and the indicator variable with value of 1 for the period after electrification (*Electrified*). The unit of analysis is a county c and decade t. Counties are consistent over time, fixed at the 1900 borders. The dependent variable is the total number of workers employed in occupations related to the provision of local public services, per 1,000 inhabitants. The occupations are teachers, doctors, policemen, firefighters, and public administrators. The variable *Electrified* indicates the treatment: a county c is considered as "treated" in decade t if it is electrified. Once a county gets treated, it remains treated for the following periods. The estimated of *Perc. Immigrant* indicates the relationship between the county share of immigrant population and employment in occupations related to the provision of public services, in non-electrified counties. The estimated coefficient of the interaction term *Perc. Immigrant* × *Electrified* indicates how this relationship differs in electrified counties relative to non-electrified counties. In column 1, the regression is run on the full sample of counties. In columns 2–5, results are reported by **county characteristics**: in columns 2–3, the share of employment in manufacturing in 1900 (calculated from the individual full-count census); in columns 4–5, the share of county employment in manufacturing industries with high energy intensity in 1900, calculated as the ratio of average energy expenses to the value of production (calculated from census of manufacturers). High/low is defined as above/below the median, considering all counties in the year of reference. All estimation models include: (i) county FEs, (ii) state × decade FEs, (iii) the county population in 1900 × decade dummies as control, and (iv) the county share of employment in manufacturing in 1900 × decade dummies as control. Estimates are weighted by the manufacturing share of employment in the county. In all estimation models, the sample excludes counties with population levels in the year 1900 above the 99th percentile of the distribution (29 counties that host the largest U.S. cities, which are considered as "always treated"). Standard errors are clustered at the county level and are reported in parentheses below the coefficients. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: DID results: Electrification and cultural assimilation of immigrant manufacturing workers

	County-decade level analysis	
	Households with at least one spouse in manufacturing	
	Native + foreign spouses	Both foreign-born spouses
	Foreign-Native Intermarriage Rate	*Foreignness Children Names*
	(1)	(2)
Electrified	0.012*	0.004
	(0.007)	(0.007)
Observation N	13,128	7,663
Cluster N	2,752	2,453
Outcome Mean_{1900}	0.107	0.460
Outcome $\text{Mean}_{\text{Non-treated}}$	0.061	0.456
County FE	✓	✓
State × Decade FE	✓	✓
County $\text{Popul.}_{1900} \times \mathbb{I}_t$	✓	✓
Manuf. $\text{Share}_{1900} \times \mathbb{I}_t$	✓	✓
Clust. SE: County_{1900}	✓	✓
Pre-trend Test: F-stat	0.830	0.987
$\beta_{h<0} = 0$ [p-value]	[0.477]	[0.398]

Note: This table reports the difference-in-differences (DID) coefficients estimated with the imputation method by Borusyak et al. (2024). The estimated coefficient is the difference between treated and control units in the post-treatment period (i.e., the average treatment effect on the treated, or ATT). The unit of analysis is a county c in a decade t. Counties are consistent over time, fixed at the 1900 borders. The dependent variable is reported at the top of the table: in Column (1), the foreign-native intermarriage rates, as the fraction of marriages with at least one U.S.-born spouse celebrated in the last decade; in Column (2), the average foreignness index of names given to children born in the U.S. in the last decade to foreign-born parents. The variable *Electrified* indicates the treatment: a county c is considered as "treated" in decade t if it is electrified. Once a county gets treated, it remains treated for the following periods. All estimation models include: (i) county FEs, (ii) state × decade FEs, (iii) the county population in 1900 × decade dummies as control, and (iv) the county share of manufacturing employment in 1900 × decade dummies as control. The sample excludes counties with population levels in the year 1900 above the 99th percentile of the distribution (29 counties that host the largest U.S. cities, which are considered as "always treated"). Estimates are weighted by the manufacturing share of employment in the county. Standard errors are clustered at the county level and are reported in parentheses below the coefficients. The table reports the F-statistics and the corresponding p-value (in square brackets) of the direct test for the hypothesis that all pre-treatment coefficients are jointly = 0 ($\beta_{h<0} = 0$, where $h = 0$ indicates the period in which treatment starts). Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.