Military Procurement and the Big Push: The Long-Run Effects of the Civil War

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Abstract

Can a large, temporary demand shock trigger lasting industrialization? I investigate this question using quasi-random variation in the placement of Quartermaster (QM) facilities during the U.S. Civil War, tracing affected counties from 1820 to 2000. Wartime procurement generated broad-based demand across metals, textiles, leather goods, and machinery, incentivizing a wave of manufacturing firm entry that had large and persistent effects: within three to four decades of the end of the war, treated counties experienced sustained gains of approximately 50 percent in manufacturing employment, 25 percent in population, and 40 percent in total county revenue relative to comparison counties. Consistent with a supply-side linkage mechanism, establishment growth outpaced population growth, the expansion operated on the extensive margin, more firms and product variety rather than larger plants. Manufacturing's contribution to county output increased substantially, income per employee rose by 14 percent, and technical patenting grew with little effect on agricultural patents. Individuals in treated counties exhibit greater upward occupational mobility concentrated among the most disadvantaged households; these gains are entirely place-based, disappearing among movers. The nature of the intervention matters: QM sites exhibit long-run persistence while narrowly specialized Ordnance sites do not, confirming that the breadth of supply-side linkages determines whether a temporary shock becomes self-sustaining. I rationalize these findings with a quantitative spatial model in which supplier-network formation generates S-shaped entry costs, multiple steady states, and the possibility of permanent transitions from a low-activity trap to a self-sustaining industrial equilibrium.

1 Introduction

What role can government play in accelerating industrialization? This is among the oldest and most consequential questions in development economics. Beyond trade protection and regulation, the classical literature offers two influential perspectives on how government action can overcome the barriers to industrial development (Scitovsky, 1954, List, 1909, Rosenstein-Rodan, 1943, Hirschman, 1958). These two perspectives share a deeper common logic: both imply that a coordination failure prevents industrialization, but that once overcome, the process becomes self-sustaining. Rosenstein-Rodan, 1943 argued that industrialization requires a coordinated "Big Push", simultaneous investment across a complementary system of *wage-goods* industries, so that the wages paid by each sustain demand for the products of the others. These *demand complementarities*, he argued, are a special case of external economies. Hirschman, 1958, by contrast, proposed that growth proceeds through strategic investment in sectors with strong linkages. In Hirschman's framework, it is the *supply-side* structure of production that transmits the impulse—backward linkages generate demand for upstream inputs, encouraging suppliers to invest, while forward linkages make new intermediate goods available at lower cost, drawing in downstream users. Development is thus a sequence of induced decisions along the input–output chain.

Whether through Rosenstein-Rodan's demand complementarities or Hirschman's supply-side linkages, both perspectives predict that once a sufficient local network of interdependent firms is established, it can be self-sustaining. Yet the two mechanisms have distinct implications. Under demand complementarities, the channel runs through purchasing power, wages drive local consumption, which sustains other firms. Under supply-side complementarities, the channel runs through the production network: a region with a dense web of buyer, supplier relationships enjoys lower entry costs and higher productivity from input variety, attracting further entry and thickening the network (Marshall, 1890, Krugman, 1991, Duranton and Puga, 2003). It is this latter mechanism that this paper tests. The supply-side channel carries a distinctive empirical signature: because the mechanism operates through the production network rather than through consumer demand, firm entry should lead population growth, effects should be spatially concentrated, and growth should operate on the extensive margin, more firms and greater product variety, rather than through the expansion of incumbents. Testing these predictions requires a large, plausibly exogenous shock observed over a horizon long enough to distinguish genuine persistence from slow mean reversion (Kline and Moretti, 2013, Greenstone et al., 2010).

I exploit quasi-random variation in the placement of federal procurement facilities during the U.S. Civil War and trace the economic evolution of affected counties from 1820 to 2000. The Quartermaster department's wartime demand was broad-based, spanning metals, textiles, leather goods, machinery, and provisions across a wide range of local suppliers. I ask whether this temporary burst of government procurement set in motion the self-reinforcing supply-side dynamics that the classical literature predicts: lasting gains in industrialization, firm entry, population, income,

and individual economic mobility.

The Civil War triggered the largest fiscal expansion in nineteenth-century American history, with federal expenditures by the North totaling approximately $1.8 billion in 1860 dollars, more than twenty-five times the pre-war annual federal budget (C. D. Goldin and Lewis, 1975; Wilson, 2003). This spending was financed primarily through government debt. Three key military bureaus managed the bulk of wartime procurement: the Quartermaster (QM) Department, the Ordnance Department, and the Subsistence Department. The Ordnance Department oversaw weapons procurement, while the Subsistence Department handled food supplies. The QM Department, by far the largest of the three, was responsible for procuring or manufacturing all remaining military materiel, including clothing and uniforms, camp equipage and personal gear, transportation vehicles, draft animals and their forage, fuel, building materials, and administrative supplies, and established procurement and manufacturing facilities across Union-controlled territory that are the main focus of this paper. The QM Department aimed to distribute funding and locations broadly, but historical evidence consistently identifies the availability of supplies and logistics as the binding constraint on site placement (Meigs, 1961-62; Wilson, 2003). Facilities were sited where production was feasible, not where long-run development was anticipated. The resulting geographic pattern of wartime procurement thus provides variation in the intensity of local demand that is driven by pre-existing characteristics rather than by differential growth potential.

I compare counties where QM facilities were established, excluding major cities, to counties with similar 1860 levels of population, manufacturing capacity, and infrastructure. I implement this comparison using two approaches, a difference-in-differences design estimated by OLS and a weighted difference-in-differences using inverse probability weighting. Both yield similar results. Conditional on 1860 observables, there is no systematic relationship between QM placement and county-level economic or demographic conditions, whether the conditioning set includes only core predictors, population, manufacturing capacity, and geography, or is expanded to include market access and additional county characteristics. Counties with QM sites and comparable counties without them showed similar trends in outcomes before 1860 and had no differences in outcome levels in the decades leading up to the CW. The treated counties and the top-weighted counterfactual counties show comparable spatial patterns in terms of pre-CW railroad networks, pre-CW steamboat navigability, and other relevant geographic features, such as 19th-century portage sites, state capitals, and fall-line proximity. I observe a consistent pattern across our different analyses: parallel pre-war trends, and a postwar takeoff.

I present four main sets of empirical results. First, QM sites had a large and persistent effect on local economic development. Up to 1860, treated and comparison counties followed similar trajectories. After 1860, treated counties experienced significant growth in manufacturing employment, the number of manufacturing establishments, and population. Notably, manufacturing establishment growth outpaced population growth in the initial post-war decades, consistent with supply-side expansion in which firm entry leads and population follows. The gap between treated

and comparison counties widened steadily through the 1890s and persisted well into the twentieth century. The sectoral composition of employment growth is instructive: manufacturing, the sector most conducive to agglomeration spillovers, consistently outpaced other sectors, while agriculture's differential growth plateaued after 1870, consistent with diminishing returns to fixed land. A further finding is that the nature of the intervention matters: both QM and Ordnance counties show short-run improvements, but only QM counties, where procurement was broad-based and generated substantial firm entry, exhibit long-run persistence. Ordnance sites, which involved narrow production and created very few new establishments, show no lasting effects, confirming that it is the initial wave of diversified entry that triggers the self-reinforcing dynamics.

Second, wartime procurement triggered a local structural transformation consistent with the supply-side Big Push mechanism. Manufacturing's share of county revenue and value added rose by 7 and 6 percentage points respectively in treated counties, reflecting a durable reallocation of economic activity away from agriculture. Manufacturing revenue diverged sharply after 1860 and continued to grow through the early twentieth century, while farm revenue showed no comparable differential. This compositional shift translated into higher incomes: income per employee rose by approximately 14 percent in QM counties. Crucially, the mechanism was horizontal entry: by 1880, QM counties hosted 21 percent more distinct manufacturing industries and 48 percent more establishments than comparable counties, while average establishment size remained statistically unchanged. This extensive-margin expansion—more firms producing a wider range of specialized inputs, not larger plants—is the empirical counterpart of the horizontal innovation channel, and distinguishes the supply-side linkage mechanism from a standard demand multiplier. Consistent with the prediction that a thicker supplier base raises not only output but also inventive activity, treated counties experienced sustained growth in patenting that outpaced population growth, with the effect concentrated entirely in technical and industrial patents; agricultural patents showed no differential response, confirming that the agglomeration externality operates through manufacturing supply chains rather than through a generic scale effect.

Third, the wartime shock reshaped the industrial composition of treated counties well beyond the original procurement industries. The expansion was broad-based, with particularly strong gains in metals, machinery, chemicals, and textiles. Post-war, treated counties were more likely to host these industry. The industry-level dynamics reveal a temporal sequencing consistent with Hirschman's linkage mechanism: sectors directly tied to wartime procurement, such as metals and clothing, expanded first, while downstream industries dependent on the availability of these inputs, machinery, tools, and fabricated products, emerged later and grew more steeply.

Fourth, individuals in treated counties exhibit greater upward mobility than those in the counterfactual group. Men aged 21–30 in 1880 experienced significant gains in occupational scores in adulthood relative to their household backgrounds, with the largest gains observed among individuals from households with low 1860 occupational scores. Specifically, in treated counties, men whose 1860 household heads fell into the lowest occupational score brackets (0 to 5, 6 to 20, and 21 to 24)

exhibit the most substantial and statistically significant gains, with point estimates for the lowest tier (0 to 5) peaking at 0.75. In contrast, men from households with higher occupational scores (24 to 31 and 32 to 80) or farm-related backgrounds show no statistically significant gains. Crucially, these mobility gains disappear after conditioning on 1880 county of residence and are absent among individuals who moved away from treated counties, indicating that it is the availability of industrial opportunities at the treated location, not a portable human capital advantage, that drives upward mobility.

To rationalize and quantify[1] these findings, I build on the quantitative spatial framework of Peters, 2022. The key innovation I make is on the entry-cost side: I microfound them through a supplier-network formation process in which each prospective entrant must establish multiple buyer, supplier relationships by searching the local pool of existing firms. This generates an S-shaped relationship between the local supplier base and the probability of successful entry, and therefore a non-linear effective entry cost that falls steeply once the supplier network crosses a critical mass threshold. Below this threshold, entry costs are prohibitively high and the region is trapped in a low-activity equilibrium; above it, entry costs collapse and industrialization becomes self-sustaining. The supplier base itself is a slow-moving state variable that accumulates as an exponentially weighted average of past firm counts, so that history shapes current entry conditions. The model generates dynamics in which a temporary procurement shock can push the supplier base past the critical threshold, triggering a wave of firm entry that attracts population, which further expands market size and induces additional entry, permanently shifting the region to a higher steady state. I use the model both to discipline the interpretation of the reduced-form evidence and to quantify the relative contributions of the network friction channel, market-size effects, and spatial sorting to the observed persistence of the Civil War procurement shock.

This study contributes to five broad areas of research. First, it contributes to the literature on industrial policy and government-led industrialization. The classical theories of Rosenstein-Rodan, 1943 and Hirschman, 1958 proposed that public investment can overcome the coordination failures that trap economies in low-activity equilibria, yet credible empirical evidence has remained scarce. Recent work has made important progress—Kline and Moretti, 2013 on infrastructure investment, Greenstone et al., 2010, Lane, 2025 on state-led manufacturing promotion, and Juhász, 2018 on infant-industry protection—but these settings typically involve either narrow interventions targeting a single sector or plant, or policy instruments (tariffs, subsidies) whose effects are difficult to separate from continued government support. This paper offers a complementary setting: a broad-based, temporary burst of government procurement across multiple industries that ended abruptly after the war, allowing a clean test of whether supply-side linkages can sustain industrialization *without* continued intervention. The 180-year horizon distinguishes permanent transitions between equilibria from slow mean reversion, and the contrasting null result for narrowly specialized ordnance sites provides a within-setting test of Hirschman's prediction that it is the breadth and

[1] under construction

strength of supply-side linkages that determines whether an initial stimulus becomes self-sustaining.

Second, it contributes to an empirical literature that documents examples of spatial persistence and path dependence, or lack thereof, in the aftermath of historical events. Two seminal studies in this literature present opposing evidence. Davis and Weinstein, 2002 finds that WWII bombing had only a transitory effect on city size, whereas Bleakley and Lin, 2012 find persistent effects stemming from long-obsolete natural advantages. Much of the subsequent literature has examined shocks that destroy existing activity—bombings, natural disasters, forced relocations—or shocks tied to durable locational fundamentals. This study provides evidence from a different type of shock: a purely demand-side episode of government procurement that was temporary, broad-based, and carried no permanent infrastructure or institutional legacy. The finding that even such a transient demand shock produced multi-century persistence aligns more closely with the path-dependence perspective, and suggests that a shock broad enough to seed the inter-firm complementarities that sustain agglomeration can lead to permanent economic transformation.

Third, this work adds to the extensive literature on regional development and the long-term effects of place-based interventions (Kline and Moretti, 2013; Garin and Rothbaum, 2025; Greenstone et al., 2010). A central concern in this literature is whether place-based benefits accrue to places or to people, and whether they flow to incumbent residents or to in-migrants (Austin et al., 2018). The individual-level results speak directly to this debate: gains in occupational mobility are entirely place-based—disappearing after conditioning on 1880 location and absent among movers—and concentrated among individuals from the most disadvantaged households, for whom the expansion of local manufacturing served as a ladder for upward mobility. These findings suggest that the gains from place-based interventions are fundamentally tied to place rather than portable across locations, and that they disproportionately benefit the least advantaged residents who remain.

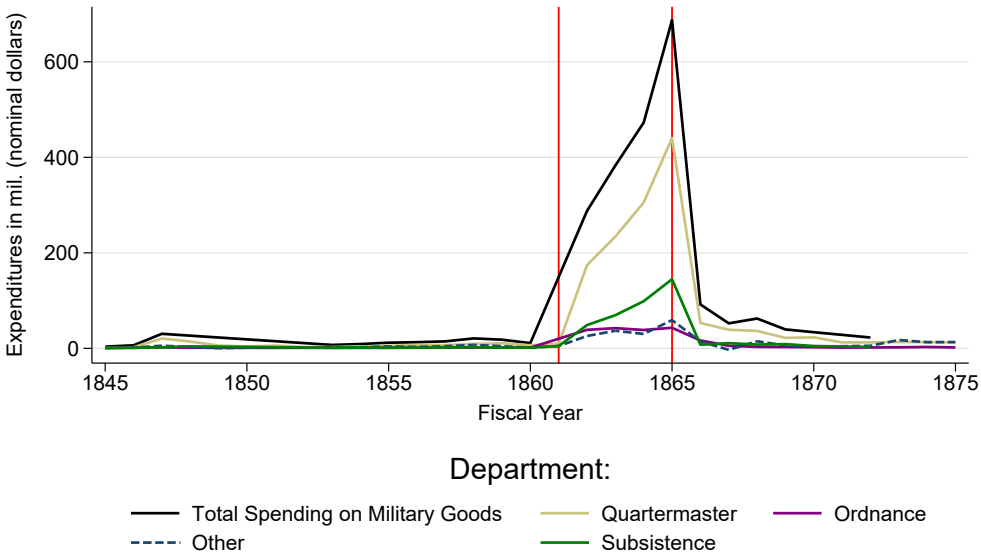
Fourth, this study contributes to the literature on the history of American economic development by analyzing a pivotal period and event in U.S. history. It highlights the critical role of war spending in shaping regional development (Gordon, 2016; Donaldson and Hornbeck, 2016; Atack et al., 2008). Additionally, the findings advance research in the geography of innovation, particularly concerning agglomeration, and contribute to the broader discourse on endogenous growth (Romer, 1986, 1990).

Fifth, it advances the literature on post-war economies, particularly in the context of the U.S. Civil War. While prior research has largely focused on the economic costs of the Civil War (C. Goldin and Margo, 1992; Feigenbaum et al., 2022; Ager et al., 2021 ;), recent studies on other conflicts have highlighted a new perspective by emphasizing the long-term effects and persistence of wartime mobilization (Fishback and Cullen, 2013; Jaworski, 2017; Gross and Sampat, 2023; Garin and Rothbaum, 2025). This study provides evidence of long-run benefits stemming from government-driven manufacturing expansions due to industrial mobilization in the U.S. North during the Civil War.

2 Historical Background

The American Civil War (1861 to 1865) was a massive economic undertaking, marked by unprecedented levels of government spending that far exceeded anything previously seen in the United States, as illustrated in Figure 1. This scale of expenditure was also extraordinary by contemporary global standards. For instance, the North's war spending was approximately four times greater than the combined expenditures of France and Britain during the Crimean War (1854–1856), one of the largest European conflicts of the time (Wilson, 2006, Wilson, 2003, Geyer and Bright, 1996). Two-thirds of all U.S. war spending was allocated to procuring the goods and services necessary to equip and sustain its forces in the field. As Porter, 1994 noted, the Northern army was *"the largest, best-equipped, best-fed, and most powerful war machine ever assembled in the history of the world to that date"* (Bensel, 1990).

Figure 1: U.S. Military Expenditures by Department, 1845–1875



Notes: This figure displays U.S. military expenditures across various departments from 1845 to 1875, in nominal dollars. The vertical red lines mark the start and end of the Civil War. Data sourced from Wilson, 2006.

During the early months of the Civil War in 1861, the Northern military economy was disorganized and highly decentralized, with the bulk of procurement occurring at the state level. Often competing for scarce resources, state officials turned to local firms for supply contracts, spending millions to outfit their regiments. However, this decentralized approach was short-lived, and by the end of 1861, the states relinquished procurement authority to national military bureaus, either voluntarily or under pressure from Washington, leading to a more centralized and organized approach to military spending.

After centralization, three bureaus primarily managed military-related spending: the Ord-

nance, Quartermaster (QM), and Subsistence Departments. The Ordnance Department oversaw the manufacturing and procurement of weapons, while the Subsistence Department handled food supplies. The Quartermaster (QM), the largest army supply bureau, led the procurement and manufacturing of all non-food and non-weapon items. This included general manufacturing goods such as clothing, tents, furniture, horses, wagons, and more. The QM Department alone spent approximately one billion dollars ($30 billion in 2024 dollars) on various military supplies.

The QM operated through a decentralized national network of sites. Under the supervision of QM officers, these sites procured goods from private firms and managed large public facilities that produced goods for military use. QM officers saw public enterprises as a way to avoid inflated prices from contractors or exploitation of the government, providing a more cost-effective solution. By 1865, the QM employed an estimated 130,000 civilian workers, including teamsters, laborers, blacksmiths, and others, with around 10,000 of these employees being women. (Weigley, 1959)

Clothing was the most expensive category of manufactured goods used by Civil War armies, and sewists formed the largest workforce in the Northern military-industrial sector. Throughout the war, the army directly employed thousands of seamstresses, who produced nearly a quarter of the garments supplied to Union forces. In the final year of the war, the Quartermaster's Department manufactured approximately 30% of the finished garments and 20% of the tents it acquired within its own facilities (Quartermaster, 1861-65, Risch, 1962). During the war, supply officers faced the immense challenge of equipping and sustaining an army of one million men. The scale of this task meant their decisions carried significant economic and political weight. From 1861 to 1865, quartermasters gained unprecedented authority, emerging as major manufacturers, employers, and buyers, and playing a pivotal role in shaping business, labor, and government during the Civil War.

The Ordnance Department produced and procured weapons at multiple sites, though these were fewer in number compared to those of the Quartermaster (QM) Department. Most of these sites were located away from densely populated areas, as security was the primary concern. Nearly all of these facilities were already under the control of the Ordnance Department prior to the CW; they simply increased production significantly to meet wartime demands.

The Subsistence Department managed the procurement of food-related supplies through local offices, which primarily coordinated procurement at the state level. As a result, spending was not localized but spread across the state, reflecting the nature of procurement activities which primarily included acquiring farm produce.[2] These offices were typically situated in state capitals or major cities[3].

The North's depot-arsenal system, which employed tens of thousands of workers and spent millions of dollars monthly, functioned as a national supply network managed by U.S. officers.

[2]From Annual Report of The Secretary of War *"Purchasing and depot commissary of subsistence at New York, N. Y., and in general charge of the subsistence department in the States of New York and Connecticut, and in New Jersey as far south as Princeton."*

[3]The locations included Washington DC, Philadelphia, New York, Detroit, Saint Louis, Louisville, Baltimore, St. Paul, and Boston.

This system operated largely independently of state and local control. Early in the war, people in the North recognized that the location of the army's supply system, particularly the Quartermaster (QM) purchasing sites and manufacturing centers, would significantly influence their local economies. As a result, members of Congress, senators, governors, and other public figures or organizations from various northern states regularly lobbied federal government officials, including the chief of the Quartermaster Department, to secure a larger share of war-related spending. (Wilson, 2006)

When it came to the decision of establishing one of these sites, the final authority rested with the military bureaus. The QM department aimed to *"distribute"* the business of clothing and equipage manufacturing "*over the different parts of the country as far as possible*". However, when it came to making actual decisions about funding distribution and site establishment, certain constraints limited the bureau's ability to spread the system widely. The primary factors influencing the final location of QM sites were "availability & cheapness of supply (resources)". (Meigs, 1862, Wilson, 2006) Additionally, the relative location of sites played a role in funding decisions. As the war progressed, the army increasingly relied on sites closer to the front lines, such as Washington, Louisville, Nashville, and New Orleans.

3 Data

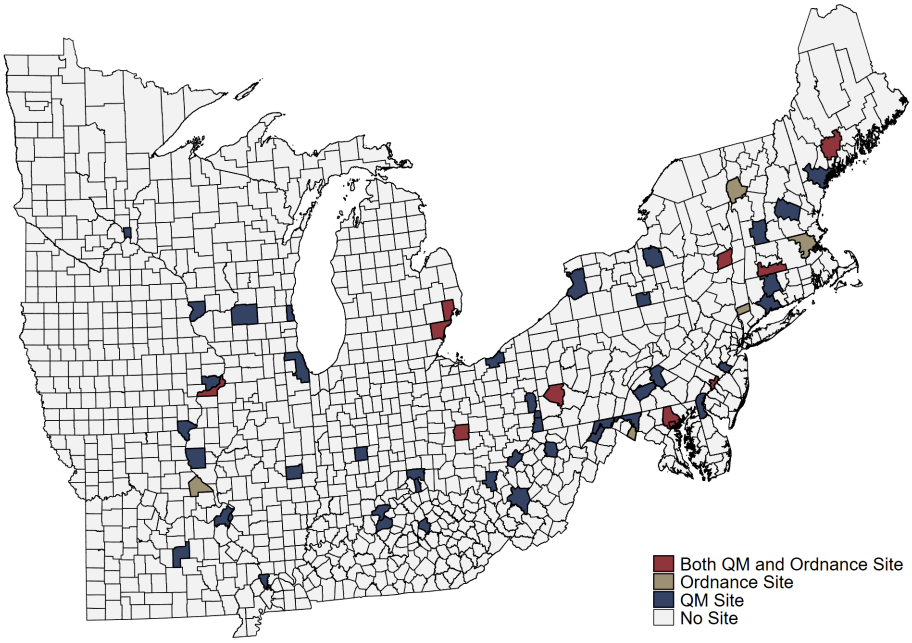
3.1 CW Location and Funding Data

To examine the impact of the event at both the county and individual levels, I utilize new data on the locations of Quartermaster sites, Ordnance sites, subsistence stations, military posts, and military hospitals during the Civil War. This data is sourced from the Annual Reports of the Quartermaster, Ordnance, and other military departments of the Union government.

The data on the locations of Quartermaster (QM) sites are digitized from the *Annual Report of the Quartermaster Department 1961-66*, supplemented by quartermaster reports from individual states. These reports offer comprehensive data on total spending across various products, consolidated at the fiscal year level. However, they provide limited details on individual sites. Reports prior to 1865 include only consolidated annual figures. In contrast, the 1865 report is more detailed, offering information on individual sites, including their locations and spending on livestock. Nevertheless, data on the quantities manufactured or purchased at these sites are available for only a few select locations. As a result, the primary treatment definition I use is whether a county had a QM site during the Civil War.[4]

[4]Excluding counties containing major cities, such as New York City, Boston, Chicago, Pittsburgh, Philadelphia, St. Louis, Baltimore, and Cincinnati.

Figure 2: Location of QM and Ordnance Sites



I collected data on the locations of arsenals and armories from the *Report of the Chief of Ordnance (1866)*. Additionally, I obtained information on the locations of subsistence stations, military hospitals, and war posts from the *Annual Reports of the Secretary of War to the U.S. Congress (1863–66)*.

3.2 County level Outcome Data

This study uses county-level outcome data from 1820 to 2000, obtained from two main databases: IPUMS-NHGIS for the years 1820–1940 and the Inter-university Consortium for Political and Social Research (ICPSR) for the period 1940–2000. The original source of these datasets is the US Census. To maintain consistency across time periods, county boundaries were adjusted to match the 1990 delineations, following the methodology outlined by Eckert et al., 2020. Additionally, the study incorporates variables describing various geographical features, derived from the dataset compiled by P. V. Fishback et al., 2005. The canal and railroad geographic data are based on shape files prepared by Atack (2015) and Atack (2016), respectively.

The canal and railroad geographic data are based on shape files prepared by Atack, 2015 and Atack, 2016, respectively. Data on fall line is from Bleakley and Lin, 2015. The data on portage sites between great lakes and navigable in the mid-west is obtained form Semple, 1903. Data on CW enlistment, causalities, injuries and disabilities is from Dupraz and Ferrara, 2023.

Sample Restrictions: The final sample includes data from 22 U.S. states. Connecticut, Delaware,

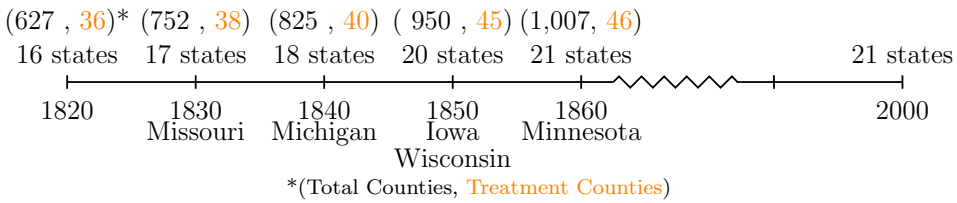


Figure 3: Sample Structure

Illinois, Indiana, Iowa, Kentucky, Maine, Maryland, Massachusetts, Michigan, Minnesota, New Hampshire, New Jersey, New York, Ohio, Pennsylvania, Rhode Island, Vermont, West Virginia, Wisconsin. Data on U.S. territories are either unavailable or highly unreliable (Eckert et al., 2020). I add counties as they become part of the union. The county numbers are conditional on the availability of relevant data for a particular census-year and do not include counties with major cities: New York City, Boston, Chicago, Pittsburgh, Philadelphia, St. Louis, Baltimore and Cincinnati. I also exclude counties with no manufacturing employment in 1860.

3.3 Individual-Level Data

I use full-count census data for decades 1860 and 1880[5] (Ruggles et al., 2020) along with the across census individual links provided. The method used to create cross census links is provided in Helgertz et al., 2021. This method links individuals across census years using a systematic, multi-step process to ensure accurate and reliable matches. It begins by selecting males from the earlier census (Census A) and pairing them with potential matches in the later census (Census B) based on strict criteria: identical sex and place of birth, birth years within +/- three years, and name similarity measured by adjusted bigram agreement and a Jaro-Winkler score above 0.7. A logistic regression (logit) model predicts the similarity between each Census A individual and potential Census B matches, incorporating individual, household, and contextual characteristics to enhance accuracy. Matches are confirmed if the predicted similarity exceeds a threshold (α) and the top match's score (α_1) surpasses the second-best match's score (α_2) by a specified margin (β). The model's parameters and thresholds are calibrated using training data, which also estimates the linkage quality in terms of precision and recall. Finally, duplicate matches are removed to ensure each individual in Census A links to only one individual in Census B.

The census also provides information on the relationships between individuals within the same household. By observing a person in their parents' household during childhood (or in the 1860 census), I can assign family background information to that individual in adulthood if they are linked to the 1880 census. I transfer household data, such as the head of household's county of residence, wealth, occupation score, and other relevant details. This information allows me to control for family background when analyzing social mobility. The primary outcome of interest is

[5]Data for 1890 is unavailable.

occupational income scores. Since the census does not offer a continuous measure of income before 1940, researchers have used occupational income scores as a proxy. The most widely used version, known as *occscore*, reflects the median total income of individuals in a given occupation as of 1950

4 Conceptual Framework

To organize the empirical analysis, I develop a simple model of regional manufacturing in which a temporary demand shock can trigger a permanent transition to a higher level of industrialization. The model combines variety-driven productivity gains from intermediate inputs with a network friction governing the cost of firm entry. Together, these features generate multiple steady states, so that a sufficiently large procurement shock can push a county from a low-activity equilibrium to a permanently more industrialized one.

Environment. Consider discrete regions $r \in \{1, \ldots, R\}$, a single manufacturing sector, and myopic agents. Consumers have CES preferences over manufacturing goods from different origins. Within each region, manufacturing output combines a continuum of intermediate varieties using a CES technology with elasticity $\rho > 1$:

$$Y_{rM,t} = Q_{r,t} \left(\int_0^{N_{r,t}} x_{rt}(i)^{(\rho-1)/\rho} \, di \right)^{\rho/(\rho-1)},$$

where $N_{r,t}$ is the measure of varieties available locally and each variety is produced by a single firm using labor: $x_{rt}(i) = h(i)$. Symmetry implies $Y_{rM,t} = Q_{r,t} \, N_{r,t}^{1/(\rho-1)} \, H_{rP,t}$. The term $N_{r,t}^{1/(\rho-1)}$ captures variety-driven productivity gains: a wider range of specialized inputs raises output even holding labor fixed. This is the horizontal innovation channel of Romer, 1990—each new variety complements rather than displaces existing ones, so productive knowledge is embodied in the count of available varieties.

Network frictions and entry. To enter, a firm must pay a fixed labor cost that depends on the local supplier base $A_{r,t}$:

$$h_{r,t}^E = \frac{f_E}{\Pi(A_{r,t})},$$

where $\Pi : \mathbb{R}_+ \to [0, 1)$ satisfies $\Pi(0) = 0$ and $\lim_{A \to \infty} \Pi(A) = 1$. Establishing a new firm requires forming relationships with suppliers of materials, components, and services; when the local network is thin, this is costly and uncertain, but as the network thickens, effective entry costs fall. The supplier base evolves as $A_{r,t} = (1 - \eta) \, A_{r,t-1} + \eta \, N_{r,t-1}$, so that today's network is built from yesterday's industrial activity, introducing path dependence.

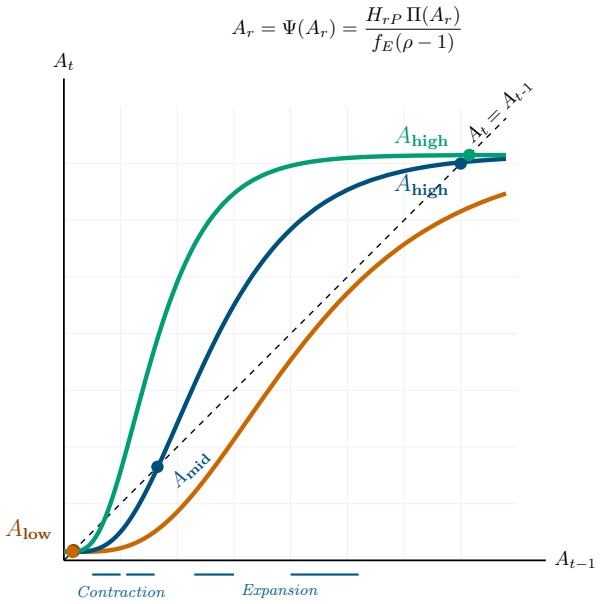


Figure 4: Fixed-Point Diagram

Multiple steady states and the Big Push. Free entry equates average firm profit to the effective entry cost. In steady state ($N_r = A_r$), this reduces to a fixed-point equation:

$$A_r = \Psi(A_r) \equiv \underbrace{\frac{\bar{H}_r}{f_E(\rho-1)}}_{\text{Market size}} \cdot \underbrace{\Pi(A_r)}_{\text{Network S-curve}} .$$

Because Π is S-shaped, Ψ can intersect the 45-degree line at multiple points (Figure 4), generating a low-activity trap and a self-sustaining high-activity equilibrium. This structure provides a supply-side microfoundation for the classical Big Push hypothesis Hirschman, 1958. The coordination failure arises on the supply side: firms need each other's presence *as suppliers* to make entry affordable. The S-shaped Π embodies the nonlinearity at the heart of the Big Push, below a critical mass the region is trapped; above it, industrialization is self-sustaining.

The procurement shock as a Big Push. The QM shock maps naturally onto this framework. Before the war, many treated counties sat near but below the critical mass threshold—possessing some manufacturing infrastructure (hence the QM department's selection) but not enough to sustain self-reinforcing agglomeration. In terms of Figure 4, these counties were positioned on the lower segment of the medium (blue) S-curve, where $\Psi(A_r)$ lies below the 45-degree line and the economy contracts toward A_{low}. Wartime demand raised $N_{r,t}$, expanding $A_{r,t}$ through the law of motion and pushing these counties past A_{mid}—the unstable threshold—into the expansion region where $\Psi(A_r)$ lies above the 45-degree line. Once past this tipping point, the self-reinforcing dynamics carried the economy toward A_{high} permanently, even after procurement ended. The key

distinction from a standard multiplier effect is *permanence*: rather than a temporary displacement that slowly reverts, the economy transitions from one steady state to another, and the gains persist even after the shock ends because the county now rests in a different basin of attraction.

This framework yields several testable predictions. The treatment effect should be persistent, since counties that cross the threshold lock into the high-activity equilibrium. The response should be concentrated in firm entry on the extensive margin, since the mechanism operates through reduced entry costs. Firm creation should lead population growth. Production, capital, employment, and intermediate inputs should expand proportionately, reflecting horizontal variety expansion rather than capital deepening. The effect should be largest for moderately developed counties near the threshold. And because the mechanism is place-based—tied to the local supplier network—individuals should benefit only insofar as they remain in the treated location. I now turn to the data to evaluate these predictions.

5 Empirical Strategy

The study focuses on local military facilities operational during the CW, including QM sites, Ordnance sites, and war posts. QM sites were essential for manufacturing, procuring, and storing general goods. Ordnance sites and armories handled the production and storage of weapons and ammunition. War posts served as assembly points for troops in various Northern states, dispatching soldiers to different fronts. The studies main focus is QM sites for the following reasons. First, the QM department accounted for the majority of federal wartime expenditures (See Figure 1). Secondly, the spending by the Quartermaster's Department is highly relevant to the long-term manufacturing development of the local economies where it was located, as it primarily focused on general manufacturing goods such as clothing, equipment, furniture, wagons, etc. I do examine ordnance sites in detail, and the nature of the sites seems to have important implications for long-term treatment effects.

The Subsistence department sites are excluded from the analysis for two main reasons: First, they were primarily located in major cities, which I have excluded from my analysis. Second, these Subsistence stations existed solely to coordinate food procurement efforts, while the actual procurement was distributed widely across various union states with no localized treatment.

The main empirical task is to examine the effects of regional government intervention during the U.S. Civil War on long-term regional development. To accomplish this, I leverage regional variation in government intervention driven by the presence of QM sites in certain areas but not others. The core assumption is that U.S. counties with an established QM site during the Civil War likely received a disproportionately larger share of government investment. However, the analysis is complicated by the selection process involved in choosing site locations, which may have been influenced by economic, political, or strategic factors. As illustrated in Figure 8, counties with QM sites generally had larger populations, higher manufacturing employment and output, better

infrastructure connectivity, and other advantages. If counties with QM sites are fundamentally different from those without, a direct comparison between the two would introduce bias.

Historical evidence indicates that national military bureaus primarily oversaw the manufacturing and procurement processes, aiming to distribute funding and locations widely. However, they consistently cited resource availability as a key constraint in their decision-making (Meigs, 1961-62, Wilson, 2003). In this analysis, I account for these constraints and use the remaining plausibly random variation to estimate the parameters of interest. The main factor limiting site locations was access to essential resources, such as workforce, infrastructure, and manufacturing capacity. I compare counties—excluding major cities—where QM sites were established to other counties with similar population, manufacturing, and infrastructure characteristics as of 1860.

To conduct this comparison, I define counties with QM sites as the primary treatment group, excluding counties with major metropolitan regions such as New York City, Boston, Chicago, Pittsburgh, Philadelphia, St. Louis, Baltimore, and Cincinnati. In the baseline sample, 47 counties are classified into the primary treatment group, with 1006 in the comparison group. **??** shows the locations of the treatment and ipw weights for comparison group.

5.1 County Level Impact

I compare counties where QM sites were established with counties that had similar population characteristics and manufacturing capacity in 1860. In the baseline specification, I control for the log of population, the share of urban population, the log of manufacturing capital, the log of manufacturing establishment count, a railroad access dummy, and basic geographic characteristics[6]. Additionally, I test whether the results are sensitive to conditioning on a more or less extensive set of covariates. The most extensive set of covariates includes the log of population and its square, the share of urban population and its square, the interaction of the log of population and the share of urban population, the log of manufacturing capital, the log of manufacturing establishment count, an indicator for railroad access, an indicator for inland steamboat navigation, an indicator for the Great Lakes, the log of total employment, the log of manufacturing employment density and its square, the log of market access, the change in the log of market access between 1850 and 1860, latitude and its square, longitude and its square, the interaction of latitude and longitude, and other geographic variables such as those for coasts, lakes, rivers, streams, beaches, and bays.

To conduct county-level comparisons, I employ two methods: OLS with covariates and propensity score reweighting. The average treatment effects on the treated (ATET), estimated using propensity score reweighting, are nearly identical to the OLS regression estimates (Słoczyński, 2022). Since the presence of a QM site may have spillover effects on adjacent areas, I also analyze the impact on neighboring counties. Furthermore, I estimate the effects using different sample restrictions and treatment definitions. I provide more details on robustness checks in the results

[6]These include variables for coasts, lakes, rivers, streams, beaches, and bays.

section.

5.1.1 OLS

I estimate impacts at the county-level with regressions of the form:

$$Y_{ct} - Y_{c,1860} = \alpha_t + \boldsymbol{\tau_t}.d_c + \lambda_t{}' X_c{}^{1860} + \epsilon_{ct} \tag{1}$$

in the equations above, Y_c is a county-level outcome, $Y_{c,1860}$ is the county level outcome in year 1860, d_c is the primary treatment variable, and $X_c{}^{1860}$ is a vector of 1860 level county covariates.

The main identification assumption[7] the following conditional independence assumptions:

$$\Delta Y_{0c,t}, \Delta Y_{1c,t} \perp d_c | X_c^{1860}. \tag{2}$$

where $Y_{0c,t}$ denotes the outcome level for year t in untreated state, $\Delta Y_{0c,t}$ denotes the change in an outcome variable from 1860 level to some other year t in untreated state, d_c is an indicator for whether county had a QM site during the Civil War and $X_c{}^{1860}$ is a vector of county-level characteristics.

I also estimate the regression using levels as the outcome instead of differences to demonstrate the evolution of the outcome before and after the intervention. The results (see Figure A.21) indicate that similar effects are observed in both the level and difference regressions.

5.1.2 Propensity Score Reweighting

In this second method, given the large initial differences in treated and non-treated counties, I use propensity score reweighing to design a more comparable counterfactual group for the treated counties. (Figure 8). Main assumption is that conditional on access to basic resources, the selection of QM locations was influenced primarily by immediate strategic factors and independent of other latent determinants of post-war economic development. Let county c's potential outcome change if treated be $\Delta Y_{1c,t}$ and its potential outcome change if untreated is $\Delta Y_{0c,t}$, then

$$\Delta Y_{0c,t}, \Delta Y_{1c,t} \perp d_c | X_c^{1860}. \tag{3}$$

where $\Delta Y_{c,t}$ denotes the change in an outcome variable from 1860 to some other year t, d_c is an indicator for whether county had a QM site during the Civil War and $X_c{}^{1860}$ is a vector of county-level characteristics.

[7] assuming functional form of regression being correct

Unconfoundedness assumption further implies (Rosenbaum and Rubin, 1983) that

$$\Delta Y_{0c,t}, \Delta Y_{1c,t} \perp d_c | Pr(d_c = 1 | {X_c}^{1860}). \tag{4}$$

I construct control group of counterfactual counties with similar suitability using an inverse probability weighting (IPW) estimator.

I first estimate a probit regression of d_c on the covariate set ${X_c}^{1860}$,

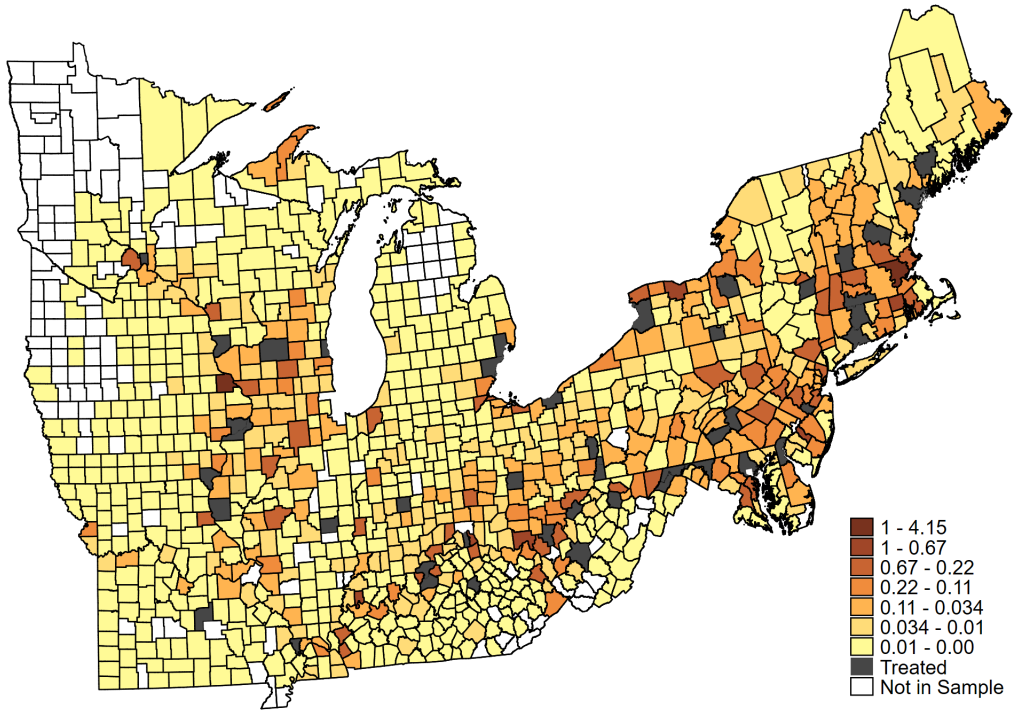
$$Pr(d_c = 1 | {X_c}^{1860}) = \phi(\beta {X_c}^{1860}) \tag{5}$$

with $\hat{p_c} = \phi(\hat{\beta} {X_c}^{1860})$ being the fitted model. I employ IPW estimator from Hirano and Imbens, 2001 to estimate ATET. The propensity score weight W_c equals one for all treatment observations, and is $W_c = \frac{\hat{p_c}({X_c}^{1860})}{1-\hat{p_c}({X_c}^{1860})}$ for control counties. The estimator being:

$$\widehat{ATET}_t = \frac{1}{N_{\mathrm{d}=1}} \sum_{c:\mathrm{d}_c=1} \Delta Y_{ct} - \frac{\sum_{c:\mathrm{d}_c=0} \Delta Y_{ct} W_c}{\sum_{c:\mathrm{d}_c=0} W_c} \tag{6}$$

ΔY_{ct} denotes the change in an outcome variable from 1860 to some other year t.

Figure 5: IPW County Weighting



Notes: The map displays 46 counties in the primary treatment group as defined in text, shaded in dark gray, and the comparison group of counties is displayed in light gray. The white-colored counties are not part of the estimation sample; they represent counties with major cities or counties with no population or manufacturing employment in 1860.

6 County-Level Effects of Wartime Spending

6.1 Baseline Estimates

To compare treatment and control counties over time, I estimate Equation 1 and Equation 6 separately for each year in which county-level outcomes are observed, using alternative covariate specifications.[8] The results, plotted in Figures 10 - 12, demonstrate that the presence of QM sites during the Civil War dramatically and persistently affected local manufacturing activity and regional development more broadly. The patterns that emerge align closely with the predictions of the conceptual framework: a temporary procurement shock expanded the local establishment base, lowered effective entry costs through the network frictions channel, triggered firm creation that preceded population growth, and ultimately pushed treated counties onto a permanently higher steady state of manufacturing activity.

Identification and covariate balance. The credibility of the empirical design rests on the assumption that, conditional on observable pre-war characteristics, treated and control counties would have followed similar trajectories absent the Quartermaster shock. Figure 8 provides direct evidence in support of this assumption. Panel (a) reports OLS coefficients from regressions of pre-war county characteristics on the treatment indicator under alternative covariate specifications; panel (b) reports propensity-score-reweighted differences. Across a wide range of covariates—population characteristics (log population, urban share, foreign-born share, racial composition, literacy), manufacturing activity (log establishments, log employment, manufacturing share, capital intensity, wages), infrastructure (railroad access, steamboat navigation, market access), land markets (land values, real estate values, farm cash values), and war-related variables (enlistment rates, casualty shares)—the conditional differences are small and centered on zero under the baseline specification. Notably, while unconditional differences exist for some manufacturing and infrastructure variables—reflecting the QM department's deliberate selection of counties with existing industrial capacity—these differences largely vanish once the baseline covariates are included, providing reassurance that the covariate set adequately captures the selection mechanism described in the historical sources (Meigs, 1961-62, Wilson, 2003).

Beyond the statistical balance documented in Figure 8, Figure 9 provides a visual comparison of key geographic and structural characteristics across treated and top-weighted comparison counties. Panel (a) superimposes portage sites, steamboat navigation routes, and the fall line onto a map of treatment and comparison counties; both groups are situated in close proximity to navigable waterways and are similarly distributed relative to historically important transshipment points, confirming that the comparison group is not systematically disadvantaged in access to pre-railroad transport infrastructure. Panel (b) maps counties with an urban share of at least

[8] Each point estimate is obtained from a separate regression. Outcomes are differenced over their 1860 levels. Standard errors are clustered at the state level.

25% in 1860: treated and comparison counties overlap substantially in their degree of urbanization, with both groups concentrated in the industrializing corridors of the Northeast and Midwest. Panel (c) overlays the 1863 railroad network onto the two sets of counties, showing that treated and top-weighted comparison counties are embedded in similar portions of the rail network—both are well-connected nodes rather than peripheral locations, consistent with the conditional balance in railroad access documented above. Finally, panel (d) plots state capitals, which are distributed across both treatment and comparison groups without systematic concentration in either, mitigating concerns that government-seat advantages confound the estimates. Taken together, these maps reinforce the conclusion drawn from the formal covariate balance tests: conditional on the baseline controls, treated and comparison counties occupied similar positions in the economic geography of the mid-nineteenth-century United States, differing primarily in the quasi-random assignment of Quartermaster procurement activity during the Civil War.

The event-study plots in Figure 10 reinforce this finding dynamically. In the decades prior to the Civil War, the point estimates for both log population and log manufacturing employment are close to zero and statistically insignificant across all covariate specifications, confirming the absence of differential pre-trends. The estimates are particularly stable under the baseline specification, which conditions on population characteristics, manufacturing characteristics, and railroad access: the pre-war coefficients are tightly centered on zero, and the post-war effects emerge sharply after 1860. The robustness of the pre-trends to the progressive inclusion of additional covariates—from no controls, to population and urban share, to manufacturing characteristics, to the full baseline set—provides further confidence that the identifying variation is not confounded by pre-existing differential trajectories.

Main effects. The post-war effects are large, statistically significant, and remarkably persistent. By 1870, within a decade of the war's end, treated counties had already begun to pull ahead: manufacturing employment rose by approximately 20–25 log points relative to control counties, and population by roughly 10-15 log points (Figure 10). These effects continued to grow through the late nineteenth century. By 1890, relative to their 1860 levels, counties with QM sites experienced population increases of approximately 25%, manufacturing employment gains of around 50%, and growth in the number of manufacturing establishments of about 50% more than comparison counties (Figure 11, panels (a)–(f)). Total county revenue followed a similar upward trajectory, with treated counties generating significantly higher aggregate income by the 1880s and 1890s (panels (g)–(h)).

The estimates are robust along several dimensions. First, they are virtually unchanged across covariate specifications. Second, the OLS and IPW estimators yield nearly identical results across all outcomes, alleviating concerns that the findings are driven by a particular functional form assumption or by extreme propensity score weights. Third, estimating the regression using levels rather than differences as the outcome (Figure A.21) confirms that the treatment and control counties were balanced in outcome levels before the war and then diverge sharply afterward, the

same pattern visible in the differenced specification, but providing additional reassurance that the results are not an artifact of the differencing procedure.

Dynamics: firm creation leads population growth. The relative evolution of outcomes over time reveals a sequence that maps closely onto the model's causal logic. In the conceptual framework, the procurement shock initially expands the establishment base; as the effective entry costs falls; new intermediate-goods firms enter; and the resulting expansion in manufacturing employment and variety subsequently attracts population through migration. The model therefore predicts a specific temporal ordering: firm creation first, population growth second.

The data exhibit precisely this pattern. Figure 12, panels (a)–(b) plot the treatment effects on log manufacturing establishments and log population jointly, along with their difference. In both the OLS and IPW specifications, the growth in manufacturing establishments substantially outpaced population growth in the decades immediately following the Civil War. The establishment-to-population ratio—the difference between the two series—rose sharply between 1860 and 1880, indicating that the initial response to the procurement shock was disproportionately concentrated in firm entry rather than population inflow. This ratio then gradually declined as population caught up over the subsequent decades, eventually converging by the early twentieth century.

The pattern observed here is consistent with the supply-side mechanism at the heart of the model: the procurement shock reduced entry barriers by building a supplier network, making it profitable for firms to enter *before* a large workforce had assembled. Workers then migrated in response to the employment opportunities created by these new establishments. The fact that firm entry preceded population growth, rather than the reverse, provides suggestive evidence that the agglomeration externality operated through the supplier network channel rather than through a simple demand or market-size effect.

Transition to a new steady state. The model features multiple steady states separated by a critical mass threshold in the establishment base. Below this threshold, network frictions are high, effective entry costs are prohibitive, and the economy remains in a low-activity equilibrium with few manufacturing firms. Once the establishment base crosses the threshold—which the Quartermaster procurement shock plausibly achieved—the network formation probability rises steeply, entry costs collapse, and the economy transitions to a high-industrialization equilibrium with a permanently larger manufacturing sector. A key implication is that the treatment effect should not dissipate once the temporary shock ends; rather, it should persist indefinitely as the economy locks into the new steady state.

The long-run dynamics in the data are consistent with this prediction. Figure 12, panels (c)–(d) plot the treatment effects on log manufacturing employment, log population, and log manufacturing employment per capita. Several features stand out. First, the differences in manufacturing employment between treated and control counties persisted throughout the entire sample period,

remaining statistically significant well into the twentieth century. The effects show no sign of reverting to zero, even six or seven decades after the Civil War ended—a pattern that is difficult to reconcile with a temporary demand shock but follows naturally from a model in which the shock triggers a permanent transition between steady states.

Second, the dynamics of convergence between employment and population are informative about the spatial equilibrium. In the immediate post-war decades, manufacturing employment growth significantly exceeded population growth, implying a rising manufacturing employment share in treated counties. Over time, however, population gradually caught up: by the early twentieth century, manufacturing employment per capita, the difference between the employment and population series, had trended close to zero. This convergence is consistent with a standard spatial equilibrium logic: the initial manufacturing boom raised labor demand and income in treated counties, attracting in-migration.

Third, the timing of convergence is itself revealing. Treated counties grew faster than comparison counties until approximately 1890, after which the differences stabilized at a new, permanently higher level. This is consistent with a transition that unfolds over two to three decades as the supplier network builds, firms enter, and population adjusts, before settling into a new steady state. The fact that the treatment effect plateaus rather than continuing to grow indefinitely suggests that treated counties reached the upper steady state by the end of the nineteenth century and subsequently grew at the same rate as the rest of the economy, exactly the prediction of the model once the economy has completed the transition.

Balanced growth in production, capital, and intermediates. A further prediction of the model is that, in the high-activity steady state, the expansion should be driven by the extensive margin, the entry of new establishments, rather than by the intensive margin of capital deepening or technological upgrading within incumbent firms. If growth is variety-driven, then employment, capital, production, and intermediate input use should all expand roughly proportionately, reflecting the replication of similar production units across a larger number of establishments.

Figure 12, panels (e)–(f) confirm this prediction. Log manufacturing production, log manufacturing capital, log manufacturing employment, and log intermediate input expenditure all evolve in close parallel, both in the OLS and IPW specifications. The four series track each other tightly from the onset of the treatment effect through the end of the sample period, with no evidence of systematic divergence. This co-movement is striking: if the treatment had instead operated through capital deepening (raising the capital-labor ratio within existing firms) or through skill-biased technological change, one would expect the capital and production series to pull away from the employment series over time. The absence of such divergence supports the interpretation that growth was driven by the horizontal entry of new establishments with similar factor proportions, consistent with the model's variety-expansion mechanism.

6.2 Robustness

The baseline estimates could be confounded by factors correlated with both the placement of QM sites and subsequent county-level growth. In this section, I systematically address the most salient threats to identification—railroad expansion, locational fundamentals, and sample composition—and show that the results are robust throughout.

Railroads. The American railroad network expanded dramatically during the nineteenth century, including during the Civil War itself. Because railroads played a central role in reducing transport costs and driving economic growth, differential railroad expansion correlated with QM site placement could confound the treatment effect. I address this concern with several complementary pieces of evidence.

First, the selection concern is directly visible in the data: unconditional 1860 covariate differences (Figure 8) confirm that treated counties had greater railroad access, higher railroad density, and better market access than comparison counties. However, these differences disappear after conditioning on the baseline covariate set, consistent with the QM department's documented selection criteria being adequately captured by the controls. Second, I verify that the counterfactual counties identified by the propensity score are comparable in their railroad infrastructure. Figure 9c plots railroad networks in treated counties alongside those in the top-weighted comparison counties; the two sets exhibit closely similar patterns, alleviating concerns that the counterfactual group systematically differs in railroad connectivity.

Third, I directly test whether the treatment effect varies with railroad infrastructure by interacting the treatment indicator with measures of railroad access (Table 3). The average treatment effects remain broadly similar across specifications. The interaction terms, however, reveal an informative pattern: counties with *lower* railroad access and below-median market access in 1860 experienced *larger* post-war growth. This finding cuts against the railroad-driven confounding story—if anything, it suggests that the QM procurement shock was more transformative for counties that were less well-connected, consistent with the model's prediction that the supplier network externality has the greatest marginal impact in counties that are further from the critical mass threshold and for which the procurement shock provides the decisive push across it.

Fourth, I restrict the sample to counties that already had railroad access by 1860 (Figure A.27, Table 3). The treatment effect patterns remain qualitatively similar, though magnitudes are slightly attenuated—consistent with the interaction results showing that less-connected counties benefited somewhat more. Finally, I examine whether treated counties gained disproportionately in railroad-driven market access before or after the war by estimating Equation 1 with log market access as the outcome, and separately by adding time-varying market access as a control.[9] The results (Figure A.22) indicate that while a subtle trend break in market access appears after the Civil

[9]The specification is $Y_c - Y_{c,1860} = \alpha + \boldsymbol{\tau} d_c + \lambda' X_c^{1860} + (MA_c - MA_{c,1860}) + \epsilon_c$.

War—suggesting a minor contribution—market access changes do not drive the treatment effects. The coefficients on the treatment indicator remain largely unchanged after controlling for differential market access gains, confirming that railroad expansion is not the primary mechanism behind the results.

Geography and locational fundamentals. Locational fundamentals, proximity to navigable water, favorable terrain, natural harbors, are well-established determinants of the spatial distribution of population and economic activity (Bleakley and Lin, 2012, Semple, 1903) and could pose a threat to identification if they are correlated with QM site placement. All specifications control for relevant geographic features, including indicators for major rivers, lakes, coasts, bays, and streams. The more extensive covariate sets additionally include latitude-longitude polynomials and interactions, Great Lakes proximity, steamboat navigation access, and log market access.

Water navigation is a particularly relevant fundamental. Before and during the expansion of the railroad network, waterways were the primary arteries of commerce, making areas with navigation access more conducive to economic growth. Treated counties were indeed more likely to have steamboat navigation access in 1860, but this difference vanishes after conditioning on covariates. Figure 9a provides visual confirmation: a map of treatment and top-weighted comparison counties, overlaid with 1860 steamboat navigation routes, shows that both groups are located in close proximity to navigable waterways. The same map also plots portage sites and the fall line—geographic features known to influence city location due to the transport advantages they confer Bleakley and Lin, 2012. Treated counties are not selectively concentrated near these features relative to comparison counties.

State capitals present a separate concern: they tend to be disproportionately large relative to what economic fundamentals alone would predict, due to the presence of government institutions. If state capitals are overrepresented among treated counties, their growth dynamics could confound the estimates. I address this in three ways. First, Figure 9d shows that state capitals are distributed across both treatment and comparison groups, mitigating compositional concerns. Second, restricting the sample to non-capital counties (Figure A.27) yields results that remain robust. Third, interacting the treatment indicator with a state capital dummy (Table 4) leaves the main effect essentially unchanged; the interaction term is statistically insignificant and negative, confirming that capital-specific growth dynamics do not drive the findings.

Additional robustness checks. I conduct a battery of supplementary robustness exercises, detailed in subsection A.1. The treatment effect estimates from the trimmed overlap sample—which ensures adequate propensity score support—are nearly identical to the baseline for both OLS and IPW. The results survive the exclusion of the top 20 manufacturing counties by employment, the removal of state capitals, and the restriction to counties with railroad access. They are similarly robust when the sample is limited to 1850 or 1840 Union states, or to counties with steamboat

navigation access. A leave-one-state-out exercise confirms that no single state drives the findings. Finally, there may be concerns about including border and frontier states—Missouri, Kentucky, West Virginia, Delaware, and Maryland—where significant fighting occurred and selective destruction could confound the estimation. Re-estimating the treatment effects after dropping these states (Figure A.23) yields results that are broadly similar to the baseline, alleviating this concern.

6.3 Treatment Effect Heterogeneity

The effects of wartime procurement need not be uniform across all treated counties. The model generates a clear prediction about which counties should benefit most: those that are closest to—but have not yet crossed—the critical mass threshold in the supplier base. For such counties, the procurement shock provides the marginal push needed to trigger the collapse of network frictions and the transition to the high-activity steady state. Counties that are already well above the threshold would experience smaller marginal gains, as their supplier networks are already dense enough to sustain low entry costs. Conversely, counties that are very far below the threshold may receive insufficient stimulus to cross it. The model therefore predicts that the treatment effect should be largest for counties that are moderately developed, large enough to have some manufacturing infrastructure but not yet at the point where agglomeration is self-sustaining.

To explore these predictions empirically, I re-estimate the treatment effects by interacting the treatment indicator with various pre-war county characteristics and by restricting the sample in specific ways (Table 3). When examining the main effect in panel (a), the treatment effect is larger for counties with lower pre-war populations, lower manufacturing employment shares, lower employment density, and lower urbanization rates. Although the interaction terms involving continuous variables are not always precisely estimated, they consistently point in the same direction: the effects are more pronounced in smaller, less industrially developed counties. This is consistent with the model's nonlinear prediction, the procurement shock had the greatest transformative impact on counties that were below but within reach of the critical mass threshold, for which the injection of wartime demand was sufficient to seed a self-sustaining supplier network.

The infrastructure interactions in panel (b) reinforce this interpretation. The main effect is stronger for counties with lower railroad density, shorter railroad lines, and worse market access. Counties with below-median market access in 1860 benefited more from the placement of a QM site within their borders. This pattern is difficult to reconcile with a story in which the treatment effect merely proxies for infrastructure-driven advantages; rather, it suggests that the procurement shock was most valuable precisely where connectivity was weakest and the barriers to firm entry were highest—exactly where the model predicts the network friction channel to have the largest bite. Interactions with other characteristics, steamboat navigability, Great Lakes proximity, state capital status, and the presence of armories (Table 4), yield little additional heterogeneity: the main effects remain broadly consistent, and the interaction coefficients are imprecise, suggesting

that these features neither amplify nor attenuate the treatment in a systematic way.

Ordnance sites The model's mechanism operates through the formation of a diversified supplier network, a web of buyer, supplier relationships across a range of intermediate goods that lowers entry costs for subsequent entrants. This mechanism should be specific to procurement activities that foster broad-based manufacturing linkages, rather than narrow, highly specialized production. Ordnance sites, which manufactured weapons and ammunition using specialized techniques with limited applicability to civilian production, provide a natural test of this prediction.

I estimate Equation 1 separately for ordnance sites and present the results in Figure A.24. The contrast with the QM site results is striking. Ordnance sites exhibit a short-run uptick in manufacturing activity during the war years, but this effect fades almost immediately afterward, with no discernible long-run impact on either manufacturing employment or population. The absence of persistence is exactly what the model would predict: because ordnance production was highly specialized, it did not generate the diversified supplier linkages needed to lower entry costs for a broad range of civilian manufacturers. The wartime activity at these sites was effectively an enclave—it employed workers and consumed inputs during the conflict but left no lasting imprint on the local input–output network. The labor force and firms at ordnance sites could not easily pivot to general manufacturing after the war, and without the positive feedback loop between the supplier base and firm entry, the initial stimulus dissipated. This null result for ordnance sites strengthens the interpretation that the persistent effects documented for QM sites operate specifically through the supplier network channel rather than through a generic wartime spending or demand multiplier.

7 Regional Structural Change

Between 1880 and 1940, the United States underwent a profound transformation from an agricultural to an industrial economy (Eckert et al., 2023, Eckert and Peters, 2025). The results presented so far suggest that this structural transformation began earlier and proceeded more rapidly in treated counties than in the nation as a whole. In this section, I examine more closely how Civil War procurement reshaped the sectoral composition of local economies, tracing the reallocation of employment across sectors, the divergence in output by sector, and the specific industries through which the manufacturing expansion materialized. The patterns that emerge align closely with the model's horizontal variety mechanism: the procurement shock triggered firm entry on the extensive margin, expanding the range of manufacturing industries and establishments without increasing average establishment size, and thereby initiating a durable shift in local economic structure from agriculture toward manufacturing.

7.1 Employment by Sector

Figure 13 traces the evolution of employment across sectors using occupation data from the full-count census between 1850 and 1950. I derive sector-level employment from occupations recorded for the working-age population by county of residence. While the census lacks occupation information for some individuals—which could introduce measurement error—the manufacturing employment estimates obtained from this residence-based measure closely match those derived from the establishment-level Census of Manufactures, strengthening confidence in both sources.

I present estimates from two specifications. Panels (a) and (c) include adjacent counties in the comparison group; panels (b) and (d) exclude them to avoid contamination from spatial spillovers, since individuals residing in neighboring counties could commute to manufacturing jobs in treated counties.[10] Comparing across these specifications reveals that spatial spillovers affect the manufacturing employment estimates more than those for agriculture—consistent with manufacturing jobs drawing workers across county borders while agricultural employment, tied to land, remains more spatially fixed.

The sectoral dynamics reveal a clear pattern of differential structural change. Between 1860 and 1870, employment in all sectors—manufacturing, agriculture, and total—grew at higher rates in treated counties, reflecting the initial broad-based expansion triggered by wartime procurement. After 1870, however, the trajectories diverge sharply. Manufacturing employment continued to expand at a substantially faster rate than other sectors, rising to approximately 40–50 log points above the comparison group by the early twentieth century. Agricultural employment, by contrast, leveled off after 1870 in terms of differential growth, remaining close to zero throughout the remainder of the sample period. Total employment—driven primarily by manufacturing gains—grew at a rate intermediate between the two. Service employment, shown in panels (c) and (d), exhibited modest positive growth that roughly tracked population, without the pronounced divergence observed in manufacturing.

The absence of persistent differential growth in agriculture is consistent with the fixed-factor constraint emphasized in the spatial spillovers section: land is immobile, and its inelastic supply limits the extent to which agricultural employment can expand in response to a local demand shock. Manufacturing, by contrast, faces no such constraint—the model's variety-expansion mechanism allows the sector to grow through the entry of new firms without running into diminishing returns on a fixed factor. The employment share data in Table 1 confirm this compositional shift quantitatively: by 1880, treated counties had a manufacturing employment share 1.5 percentage points higher (21 percent in log terms) than comparison counties, with a corresponding—though imprecisely estimated—decline in the agricultural share.

[10] For example, an individual living in a neighboring county could work at a manufacturing firm in a treatment county, leading to biased treatment effect estimates due to spatial spillovers.

7.2 Output by Sector

The employment reallocation documented above translated into a pronounced shift in the composition of local economic output. Table 2 summarizes the key magnitudes: manufacturing's share of county revenue and value added rose by 7 and 6 percentage points respectively relative to comparison counties, reflecting a durable reallocation of economic activity away from agriculture and toward industry.

Figure 14a traces the dynamics of this transformation. Manufacturing production revenue diverged sharply from the comparison group after 1860 and continued to grow through the early twentieth century, reaching approximately 60 log points above comparison counties by 1900. Farm revenue, by contrast, showed no comparable differential—point estimates remained close to zero throughout the post-war period. The divergence between these two series captures the essence of the local structural transformation: treated counties did not simply grow larger; they grew *differently*, shifting the composition of their output toward manufacturing in a way that comparison counties did not.

These compositional shifts translated into higher incomes. Figure 14b confirms that both aggregate county revenue and revenue per employee exhibit parallel pre-trends and a sustained post-war divergence. County revenue rose steadily through the post-war decades, while revenue per employee increased more gradually, reaching roughly 15–45 log points above the comparison group by the early 1900s. Income per employee in treated counties rose by approximately 14 percent relative to the comparison group (Table 2). The fact that income per employee—not just total income—grew in treated counties indicates that the structural shift toward manufacturing was productivity-enhancing: workers in treated counties were allocated to higher-value activities, consistent with the model's prediction that variety-driven productivity gains raise output per worker.

7.3 Industry Creation

The model's central prediction is that the procurement shock lowers effective entry costs, triggering firm entry on the extensive margin, more establishments producing a wider range of varieties, rather than the scaling up of existing firms on the intensive margin. The structural change results in Table 2 provide direct support for this prediction. By 1880, QM counties hosted 21 percent more distinct manufacturing industries and 48 percent more establishments than comparable counties. Yet average establishment size, measured by either revenue per establishment or workers per establishment, remained statistically unchanged. The expansion was thus driven entirely by the extensive margin: a greater number and variety of firms, not larger individual plants.

Figure 15 disaggregates this extensive-margin expansion by industry. Panel (a) reports the effect on the probability that a given industry is present in a county (the extensive margin), while panel (b) reports the effect on the number of establishments conditional on industry presence

(the intensive margin). On the extensive margin, the effects are positive and significant across a broad range of industries, with particularly large gains in metals (primary metals, fabricated metal products, mining and smelting), machinery and engines, chemicals, and textiles. This breadth of industry creation is consistent with the horizontal variety interpretation: the procurement shock did not simply expand a single wartime industry but rather seeded a diversified supplier network that facilitated entry across many sectors. On the intensive margin, the effects are generally positive but more heterogeneous and less precisely estimated, reinforcing the conclusion that growth operated primarily through the entry of new establishments rather than the expansion of incumbents.

The industry-level dynamics in Figure 16 provide further insight into the composition of the manufacturing expansion. Panel (a) traces employment in clothing and leather goods alongside metals and metal products. Both sectors expanded significantly after the Civil War, but the metals sector exhibited stronger and more persistent growth—consistent with the idea that wartime procurement, which heavily demanded metal goods and equipment, seeded supplier relationships in metal-working industries that subsequently attracted downstream entry in machinery, fabrication, and related sectors. Panel (b) decomposes the metals category further, separating metal processing and fabrication from machinery, tools, and vehicles. Both subsectors grew substantially, but machinery and tools—a downstream industry that depends on the availability of metal inputs and specialized components—emerged somewhat later and grew more steeply, consistent with a sequential process in which upstream supplier entry facilitates downstream variety expansion over time. This temporal sequencing—upstream first, downstream following—is precisely the dynamic that the network frictions mechanism predicts: as the supplier base thickens and the cost of forming buyer–supplier relationships falls, it becomes progressively easier for downstream firms to enter, generating a cascading expansion along the input–output chain.

7.4 Spatial Spillovers and Agglomeration Shadows

Understanding how neighboring counties respond to treatment is important for two main reasons. First, spillovers onto adjacent counties could confound the baseline estimates if these counties remain in the comparison group. Second, the spatial reach of the treatment effect speaks directly to the nature of the agglomeration externality: if the network frictions channel operates through localized buyer–supplier relationships, its benefits should be geographically concentrated, potentially drawing activity *away* from nearby areas rather than diffusing outward.

Robustness to excluding adjacent counties. To assess whether spatial spillovers bias the main results, I re-estimate the treatment effect after dropping all counties that border a treated county from the comparison group. The event-study pattern, plotted in Figure A.29, remains broadly consistent with the baseline findings, indicating that the inclusion or exclusion of adjacent counties does not materially alter the estimates.

Effect on adjacent counties. I next examine the treatment's impact on neighboring counties directly. I estimate the model specified in Equation (1), replacing the treatment indicator with a dummy equal to one for counties that border a treated county and zero otherwise; treated counties themselves are excluded from the estimation sample. Figure B.1, panel (a) plots the effect on log population, and panel (b) plots the effect on log income per employee, for both treated and adjacent counties. Before treatment, the two groups display similar trajectories, suggesting no major pre-existing trend differences[11].

After 1860, the two series diverge sharply. Treated counties experience sustained population growth, while adjacent counties move in the *opposite* direction relative to the comparison group—consistent with an agglomeration shadow in which the treated counties' expanding supplier base draws workers and firms inward rather than generating positive spillovers outward. This pattern of localized concentration with negative nearby effects is a distinctive prediction of models featuring thick-market externalities and network frictions: once a county crosses the critical mass threshold at which entry costs collapse, it becomes increasingly attractive relative to its neighbors, generating a self-reinforcing spatial divergence.

The income dynamics, however, suggest that this spatial reorganization is not simply a zero-sum reallocation of activity but rather a process of *sectoral specialization* with aggregate efficiency gains. Adjacent counties, despite losing population, do not exhibit any decline in income per worker. A Roy-model interpretation helps rationalize this pattern. As the manufacturing sector in treated counties expands and pulls in workers with a comparative advantage in industrial production, neighboring counties become increasingly specialized in agriculture. The outflow of labor from adjacent counties eases pressure on the fixed factor—land—thereby relaxing the diminishing returns that would otherwise depress agricultural incomes as population grows. The workers who remain are those whose comparative advantage lies in farming, and they now operate on a more favorable land-to-labor ratio. The net effect is that per capita income in adjacent counties is sustained even as population falls: the composition shifts toward agriculture, but the gains from specialization and the relaxation of Malthusian pressure on land roughly offset the loss of any manufacturing activity. This is consistent with a broader spatial equilibrium in which the procurement shock triggers a sorting of workers across sectors and space according to comparative advantage , with treated counties capturing the increasing-returns manufacturing activity and adjacent counties specializing in the constant-returns agricultural sector. The trend reverses after 1930, potentially due to improvements in commuting. These results follow more of a logic of demand complementarities as population decline leads manufacturing decline.

[11]The event-study results for other outcomes from this specification are plotted in Figure **??**, alongside the main treatment effect for the treated counties.

8 Innovation

A key mechanism through which the supplier network externality operates in the model is the variety-driven productivity channel: as the supplier base expands and network frictions collapse, the equilibrium number of intermediate varieties rises, generating productivity gains. This logic connects directly to endogenous growth frameworks in which the proliferation of differentiated intermediate inputs drives aggregate productivity and, ultimately, innovative activity (Romer, 1990, Grossman and Helpman, 1991). In this class of models, innovation takes the form of *horizontal* expansion of variety—each new entrant contributes a specialized input that does not displace existing ones, so the stock of productive knowledge is embodied in the count of available varieties rather than in the quality of any single good. Because a larger set of specialized components, tools, and intermediate goods raises final-goods productivity, the model predicts that a thicker supplier base should be associated not only with greater output but also with heightened inventive activity. Figure 17 examines whether this channel manifests empirically by estimating the effect of Quartermaster treatment on county-level patenting. Panel (a) shows that treated counties experienced a sustained and growing increase in total patents relative to control counties, with point estimates rising from near zero in the pre-treatment period to roughly 0.30–0.45 log points by the early twentieth century. The divergence between the patent series and the population series, included as a benchmark, suggests that the innovation effect is not simply an artifact of differential population growth but instead reflects a genuine increase in inventive intensity per capita.

Panel (b) decomposes the patent measure into technical patents (mechanical and chemical) and agricultural patents. The results indicate that the treatment effect is concentrated almost entirely in technical and industrial patents, which show a pattern of persistent divergence that strengthens over time—consistent with the prediction that a thicker supplier base lowers effective entry costs and raises the returns to developing new manufactured varieties. Agricultural patents, by contrast, display no systematic treatment effect, with point estimates remaining close to zero and statistically insignificant throughout the sample period. This differential response across patent categories is precisely what the network frictions framework would predict: the agglomeration externality operates through manufacturing supply chains and the formation of buyer–supplier relationships, mechanisms that have little bearing on agricultural innovation. The pattern also resonates with the broader literature linking industrial clustering to localized knowledge spillovers and innovation (Marshall, 1890), and supports the interpretation that Civil War procurement shocks, by seeding a critical mass of suppliers, set treated counties on a self-reinforcing path of industrial deepening and technical creativity.

9 Effect on Individuals: Occupational Mobility

The county-level results established that Quartermaster sites generated persistent gains in manufacturing activity, employment, and innovation. A natural question is whether these aggregate effects translated into meaningful improvements in the economic lives of individuals who were present in treated counties at the time of the shock. In this section, I examine whether the expansion of manufacturing in QM counties led to long-term gains in occupational attainment and upward mobility for pre-war residents.

I employ the following specifications to estimate the impact on occupational scores in adulthood for white men born between 1842 and 1860:

$$OccScore_i - {OccScore_{h(i)}}^{1860} = \boldsymbol{\tau} \cdot Treat_{c(i)} + \alpha_i^{age} + \mu_i^{pob} + \lambda {X_{c(i)}}^{1860} + \epsilon_i \tag{7}$$

$$OccScore_i = \boldsymbol{\tau} \cdot Treat_{c(i)} + \alpha_i^{age} + \mu_i^{pob} + \lambda {X_{c(i)}}^{1860} + \epsilon_i \tag{8}$$

where c represents the county of residence as recorded in the 1860 census, α_i^{age} is an age/year-of-birth fixed effect, μ_i^{pob} is a state or country-of-birth fixed effect, ${X_c}^{1860}$ is the 1860 county-level covariate set, and ${OccScore_{h(i)}}^{1860}$ is the occupation score of the head of household h to which individual i belonged. An individual is defined as treated if, in the 1860 census, they resided in a county where a QM site was subsequently established during the Civil War. This specification requires a stronger conditional independence assumption than the difference-in-differences design,[12] but the balance of pre-war county-level outcomes documented in prior sections provides supporting evidence.

Since the census does not provide a continuous measure of income before 1940, I follow standard practice and use occupational income scores as a proxy for economic status. The primary measure, *occscore*, reflects the median total income of individuals in a given occupation as of 1950. The outcome of interest in Equation 7 captures social mobility: the difference between an individual's own occupation score in 1880 and that of their 1860 household head. I estimate effects for men aged 21–37 in 1880 (born 1842–1860), though some individuals in this cohort may have served in the Civil War. To address this concern, I also present results restricting the sample to those born between 1850 and 1860 (aged 21–30 in 1880); the findings are essentially unchanged.

Upward mobility. For considerations of upward mobility, it is important to examine whether the treatment effect varies with household background—that is, how much individuals gained relative to the households in which they grew up. Existing research suggests that individuals from low-income families benefit disproportionately from expanded manufacturing opportunities garin.

[12] Namely, $Y_{0c,t}, Y_{1c,t} \perp d_c \mid X_c^{1860}$.

I estimate Equation 7 separately for individuals grouped by the 1860 occupation score of their household head and present the results in Figure 18.

The estimates reveal a clear gradient. Men from the lowest-scoring households (occupation scores 0–5) experienced the largest gains in occupational mobility, with point estimates ranging from approximately 0.5 to 0.8 depending on the covariate specification. The treatment effect declines monotonically as household background improves: individuals from households with occupation scores of 6–20 show gains of roughly 0.4–0.6, while those from the highest-scoring households (32–80) and farm-related households exhibit small and generally insignificant effects. This pattern is robust across both age samples—panels (a) and (b) of Figure 18—and across all covariate specifications considered. The results are consistent with the interpretation that the expansion of the manufacturing sector in treated counties opened pathways to higher-paying industrial occupations that were particularly valuable for children from disadvantaged backgrounds, for whom such opportunities would otherwise have been scarce. At the other end of the spectrum, the near-zero effect for farm-related households echoes the Roy-model interpretation, individuals whose comparative advantage lies in agriculture do not gain from manufacturing agglomeration, consistent with sectoral sorting.

In Figure 20, I present effects on a literacy indicator. The results show small positive effects concentrated among individuals from households with middle-range occupation scores (6–20 and 21–24), while effects are negligible at both ends of the distribution. This pattern is consistent with the nature of the occupational transition involved: individuals from the lowest-scoring households could move into low-skilled manufacturing positions, where the largest occupational mobility gains were observed, without additional literacy, while those from high-scoring households were likely already literate. It is the middle group, for whom the marginal manufacturing opportunity required some skill upgrading, that exhibits the strongest literacy response.

9.1 People versus Place

What drove the positive effect on occupational mobility for individuals in treated counties? Two distinct channels could be at work. First, a *people* channel: wartime economic expansion may have made treated counties better environments in which to grow up, endowing children with skills or networks that raised their subsequent earnings regardless of where they lived as adults. Second, a *place* channel: the continued post-war economic growth documented in earlier sections may have increased the availability of well-paying manufacturing jobs in treated counties during adulthood, benefiting those who remained. The results presented in this subsection cannot be interpreted as strictly causal, because they condition on location in the 1880 census, itself a potential outcome of treatment. Nonetheless, they provide informative evidence on the relative importance of these two channels, and the distinction between them speaks directly to the model's core mechanism: if the gains are place-based rather than portable, the natural interpretation is that what matters is

the local supplier base and the low effective entry costs it sustains, precisely the network frictions channel—rather than a human capital advantage acquired during the war years.

Figure 19, panel (a) re-estimates Equation 7 for the younger cohort (aged 21–31 in 1880) after adding 1880 county-of-residence fixed effects. The inclusion of these fixed effects absorbs all cross-county variation in local economic conditions at the time outcomes are measured. After conditioning on 1880 location, the treatment effects largely disappear: point estimates fall close to zero and become statistically insignificant across all household-background categories. This indicates that the observed mobility gains were driven primarily by *where individuals were living in 1880*, that is, by the economic opportunities available in treated counties, rather than by a portable advantage acquired during childhood.

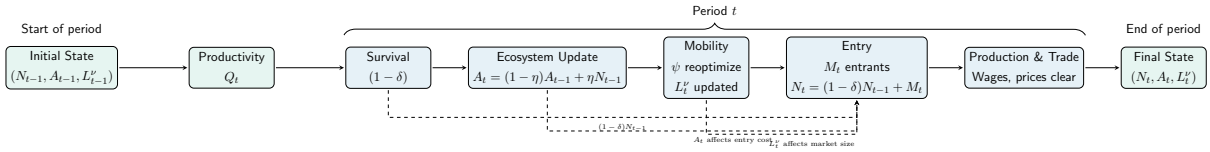
Panel (b) provides complementary evidence by separating the sample into movers (individuals who changed county between 1860 and 1880) and non-movers. Among non-movers—those who remained in their 1860 county of residence—the treatment effect is large and significant, particularly for individuals from low-occupation-score households. By contrast, among movers, the estimates for those originally in treated versus untreated counties are small and statistically indistinguishable from zero. If the treatment operated through a people channel—by improving the human capital or skills of those who grew up in treated counties—one would expect movers from treated counties to carry this advantage with them; the absence of such an effect points decisively toward the place channel. This finding is arguably the most direct individual-level test of the model's agglomeration mechanism. Workers benefit only insofar as they remain in the location where the supplier network externality operates: non-movers, who continue to access the expanding set of manufacturing opportunities sustained by low entry costs, experience significant upward mobility; movers, who leave the agglomeration behind, do not.

Taken together, the individual-level results paint a consistent picture: the persistent manufacturing agglomeration triggered by Quartermaster procurement generated tangible gains in occupational mobility, concentrated among individuals from the most disadvantaged household backgrounds. These gains were driven not by a portable human capital advantage acquired during the war years, but by the continued availability of higher-paying industrial employment in treated counties during adulthood—a finding that reinforces the central role of the place-based agglomeration mechanism documented throughout this paper.

10 Model

To rationalize and quantify[13] these findings, I build on the quantitative spatial framework of Peters, 2022. The key innovation I make is on the entry-cost side: I micro-found them through a supplier-network formation process in which each prospective entrant must establish multiple buyer, supplier relationships by searching the local pool of existing firms.

[13] under construction



10.1 Environment

Time is discrete, $t = 0, 1, 2, \ldots$. The economy consists of R regions (counties) indexed by $r \in \{1, \ldots, R\}$. There are two final consumption goods (sectors) $s \in \{A, M\}$: agriculture (A) and manufacturing (M). Individuals are myopic and take per-period prices as given; in each period they choose consumption, sector, and (if allowed) location to maximize current utility. Each location r has a fixed agricultural land endowment $T_r > 0$. The returns to land and firms accrue to a set of immobile land owners and entrepreneurs, respectively.

10.2 Preferences and Demand

Individuals have per-period consumption utility

$$u(c_A, c_M) = c_A^{\alpha}\, c_M^{1-\alpha}, \qquad \alpha \in (0, 1). \tag{9}$$

derived from consuming composite manufacturing and agriculture good. Optimal expenditure satisfies $E_{jA,t} = \alpha\, E_{j,t}$ and $E_{jM,t} = (1-\alpha)\, E_{j,t}$, where $E_{j,t}$ is total expenditure in region j.

For each sector $s \in \{A, M\}$, the composite good consumed in destination j is a CES aggregate of origin varieties:

$$Y_{js,t} = \left(\sum_{r=1}^{R} Y_{rs\to j,t}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \qquad \sigma > 1, \tag{10}$$

where $Y_{rs\to j,t}$ is the quantity of the sector-s variety from origin r delivered to destination j. Shipping from r to j incurs iceberg cost $\tau_{rj} \geq 1$ ($\tau_{rr} = 1$), so consumers in j pay $\tau_{rj} P_{rs,t}$ for origin-r goods. Cost-minimization yields the sectoral price index

$$P_{js,t} = \left(\sum_{r=1}^{R} (\tau_{rj}\, P_{rs,t})^{1-\sigma} \right)^{\frac{1}{1-\sigma}}, \tag{11}$$

and delivered demand $Y_{rs\to j,t} = (\tau_{rj}\, P_{rs,t} / P_{js,t})^{-\sigma} Y_{js,t}$.

10.3 Production Technologies

Regional productivity follows an AR(1) in logs:

$$\ln Q_{r,t} = (1-\varrho) \ln \bar{Q}_r + \varrho \ln Q_{r,t-1} + \sigma_Q\, u_{r,t}, \qquad u_{r,t} \overset{i.i.d.}{\sim} \mathcal{N}(0,1), \quad \varrho \in [0, 1). \tag{12}$$

Here $\bar{Q}_r$ is a fixed, region-specific level of innate productivity that determines the long-run level of exogenous productivity, and ϱ governs the auto-correlation.

10.3.1 Agriculture

Agricultural output in region r uses land T_r and efficiency units of labor $H_{rA,t}$:

$$Y_{rA,t} = Q_{r,t}\, T_r^{1-\gamma}\, H_{rA,t}^{\gamma}, \qquad \gamma \in (0,1). \tag{13}$$

Since agricultural land is in fixed supply, production is subject to decreasing returns to scale. The returns to land accrue to immobile landowners. The market is perfectly competitive.

10.3.2 Manufacturing

Final manufacturing good is produced by aggregating a continuum of intermediate varieties $i \in [0, N_{r,t}]$ via a CES technology:

$$Y_{rM,t} = Q_{r,t} \left(\int_0^{N_{r,t}} x_{r,t}(i)^{\frac{\rho-1}{\rho}}\, \mathrm{d}i \right)^{\frac{\rho}{\rho-1}}, \qquad \rho > 1, \tag{14}$$

where each intermediate is produced using manufacturing labor with a linear technology: $x_{r,t}(i) = h_{r,t}(i)$. The market for intermediate inputs is monopolistically competitive. Firms charge a constant markup $\mu = \rho/(\rho-1)$ and receive a share $1/\rho$ of firm revenue as profits. Production workers receive the residual share $(\rho-1)/\rho$ as labor payments. Per-firm profit is

$$\pi_{r,t} = \frac{1}{\rho} \frac{P_{rM,t}\, Y_{rM,t}}{N_{r,t}} = \frac{1}{\rho-1} \frac{w_{rM,t}\, H_{rP,t}}{N_{r,t}}, \tag{15}$$

where $H_{rP,t} \equiv \int_0^{N_{r,t}} h_{r,t}(i)\, \mathrm{d}i$ denotes the mass of production workers (excluding entry labor).

Assuming symmetry across intermediates in equilibrium ($x(i) = x$ for all i), total production labor satisfies $H_{rP,t} = N_{r,t}\, x$, so

$$Y_{rM,t} = Q_{r,t}\, N_{r,t}^{\vartheta}\, H_{rP,t}, \qquad \vartheta \equiv \frac{1}{\rho-1}. \tag{16}$$

The parameter ϑ is the *love-of-variety* exponent: a larger mass of varieties raises productivity through greater specialization (Romer, 1986).

10.4 Establishment Entry: Micro foundation for Entry Costs

To commence production, a potential entrant in location r at time t must establish $m(\geq 2)$ distinct supplier relationships (input links) with existing local firms. Each link must be individually formed

Figure 6: Function $\Pi(A)$

by searching the local supplier pool. Our microfoundation for supplier search draws on the urn-ball matching function from the labor literature Petrongolo and Pissarides, 2001. I reinterpret the matching pool as the local stock of active suppliers $A_{r,t}$ and require each entrant to successfully form m distinct supplier links, leading to an S-shaped relationship between the ecosystem stock and the probability of successful entry. The parameter m indexes the complexity of the local production network required for viable operation.

The pool from which entrants search for suppliers is the effective supplier base $A_{r,t} \geq 0$, a slow-moving stock reflecting the accumulated depth of the local industrial ecosystem (see Section - 10.5). For each of its m required links, the entrant searches the local pool. The number of viable supplier candidates for any single link type arrives as a Poisson process with rate $\lambda_{\text{match}} = \xi\, A_{r,t}/\bar{N}$, where $\xi > 0$ is a matching efficiency parameter and $\bar{N} > 0$ is a normalization constant. The probability that at least one viable supplier is found for a single link type is:

$$p(A_{r,t}) = 1 - \exp\left(-\xi\, \frac{A_{r,t}}{\bar{N}}\right). \tag{17}$$

Assuming the m links are formed independently, the probability that the entrant successfully assembles all m required links is:

$$\Pi(A_{r,t}) = \left[p(A_{r,t})\right]^m = \left(1 - \exp\left(-\xi\, \frac{A_{r,t}}{\bar{N}}\right)\right)^m. \tag{18}$$

Lemma 1 (Properties of the network formation probability)**.** *The function* $\Pi : \mathbb{R}_+ \to [0, 1)$ *defined by* (18) *satisfies: (a)* $\Pi(0) = 0$ *and* $\lim_{A\to\infty} \Pi(A) = 1$*; (b)* $\Pi'(A) > 0$ *for all* $A > 0$*; (c)* Π *has a unique inflection point at*

$$A^* = \frac{\bar{N}}{\xi} \ln m, \tag{19}$$

so Π *is S-shaped (sigmoid), with* $\Pi''(A) > 0$ *for* $A < A^*$ *and* $\Pi''(A) < 0$ *for* $A > A^*$*.*

The critical-mass threshold A^* is increasing in m (technologies requiring more complex supply chains need a denser local ecosystem before agglomeration kicks in) and decreasing in ξ (better matching technology lowers the critical mass).

10.4.1 Effective entry cost

Each entry attempt costs $f_E > 0$ efficiency units of manufacturing labor. Since the entrant succeeds with probability $\Pi(A_{r,t})$, the expected labor cost of a successful entry is:

$$h^E_{r,t} = \frac{f_E}{\Pi(A_{r,t})} = f_E \left(1 - \exp\left(-\xi \frac{A_{r,t}}{\bar{N}}\right)\right)^{-m}. \tag{20}$$

This satisfies $\lim_{A\to 0^+} h^E(A) = +\infty$ (entry is prohibitively costly when the supplier base is negligible) and $\lim_{A\to\infty} h^E(A) = f_E$ (in a maximally thick market, only the technological fixed cost remains).

Let $\tau^{\text{exog}}_{r,t} > 0$ be an exogenous policy wedge. The total effective entry cost in labor units is

$$h^E_{r,t} = f_E \, \tau^{\text{exog}}_{r,t} \left(1 - \exp\left(-\xi \frac{A_{r,t}}{\bar{N}}\right)\right)^{-m}, \tag{21}$$

and we define the composite effective entry wedge:

$$\tau^{\text{eff}}_{r,t} \equiv \frac{\tau^{\text{exog}}_{r,t}}{\Pi(A_{r,t})}, \tag{22}$$

so that $h^E_{r,t} = f_E \, \tau^{\text{eff}}_{r,t}$.

10.5 Ecosystem Dynamics

Assumption 1 (Ecosystem accumulation)**.** *The effective supplier base evolves as a partial-adjustment filter of the lagged firm stock:*

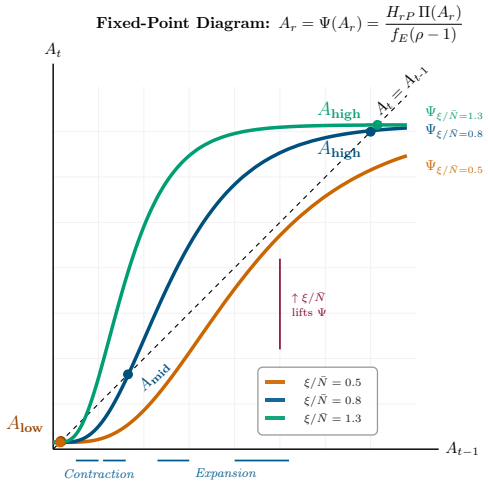
$$A_{r,t} = (1-\eta)\, A_{r,t-1} + \eta \, N_{r,t-1}, \qquad \eta \in (0,1). \tag{23}$$

Equation (23) implies that $A_{r,t}$ is an exponentially weighted moving average of past firm counts:

$$A_{r,t} = \eta \sum_{k=0}^{\infty} (1-\eta)^k \, N_{r,t-1-k}. \tag{24}$$

The parameter η governs the memory of the ecosystem: when η is small, the supplier base adjusts slowly and past firm activity persists; when η is large, the supplier base closely tracks current firm counts.

Figure 7: Steady State Behaviour



10.5.1 Path dependence from the network–ecosystem interaction

The combination of (20) and (23) generates path dependence: below critical mass, entry costs are prohibitive and the region remains trapped; near critical mass, a positive feedback loop can generate rapid industrialization; above critical mass, the ecosystem channel saturates and entry costs approach the technological minimum.

Multiple steady states: Under the network entry cost (20) and the ecosystem dynamics (23), there can exist multiple locally stable steady states for A_r when $m \geq 2$. In particular, for sufficiently large m and intermediate values of τ_r^{exog}, there exist a low steady state with $A_r^{low} < A^*$ (poverty trap) and a high steady state with $A_r^{high} > A^*$ (industrialized equilibrium).

10.6 Entry, Exit, and Variety Dynamics

At the beginning of each period, a fraction $\delta \in (0,1)$ of firms exit. Let $M_{r,t} \geq 0$ denote the mass of entrants. The law of motion for varieties is

$$N_{r,t} = (1-\delta)\, N_{r,t-1} + M_{r,t}. \tag{25}$$

Each entrant hires $h_{r,t}^E = f_E\, \tau_{r,t}^{\text{eff}}$ efficiency units of manufacturing labor. Total entry labor is $H_{rE,t} = f_E\, \tau_{r,t}^{\text{eff}}\, M_{r,t}$, and total manufacturing labor splits as $H_{rM,t} = H_{rP,t} + H_{rE,t}$.

10.6.1 Free entry

Entrants are myopic. Entry occurs if and only if per-period operating profit covers the entry cost:

$$\pi_{r,t} = w_{rM,t}\, f_E\, \tau_{r,t}^{\text{eff}}. \tag{26}$$

Substituting the per-firm profit expression (15) and solving for $N_{r,t}$:

$$N_{r,t} = \frac{1}{f_E(\rho-1)}\, H_{rP,t}\, \big(\tau_{r,t}^{\text{eff}}\big)^{-1}. \tag{27}$$

Expanding the effective entry wedge:

$$N_{r,t} = \frac{1}{f_E(\rho-1)\,\tau_{r,t}^{\text{exog}}} \times \underbrace{H_{rP,t}}_{\text{Market size}} \times \underbrace{\Pi(A_{r,t})}_{\text{Network agglomeration}}. \tag{28}$$

Equation (28) is the key equation of the model. The first term is the usual scale effect: a larger workforce triggers entry via larger profits. The second term captures the network agglomeration force: a thicker supplier base raises $\Pi(A_{r,t})$ and hence the equilibrium number of firms.

10.6.2 Market-size equation

Combining the labor identity $H_{rM,t} = H_{rP,t} + H_{rE,t}$ with the free-entry conditions yields a closed-form expression for production labor:

$$H_{rP,t} = \frac{\rho-1}{\rho}\Big(H_{rM,t} + (1-\delta)\, f_E\, \tau_{r,t}^{\text{eff}}\, N_{r,t-1}\Big). \tag{29}$$

Production labor depends positively on both the current manufacturing workforce $H_{rM,t}$ (market-size channel) and the lagged variety stock $N_{r,t-1}$ (incumbent channel), modulated by the effective entry wedge $\tau_{r,t}^{\text{eff}}$.

10.6.3 Increasing-returns production function

Substituting (27) into the love-of-variety production function (16):

$$Y_{rM,t} = \varsigma\, Q_{r,t}\, H_{rP,t}^{1+\vartheta}\, (\tau_{r,t}^{\text{eff}})^{-\vartheta}, \qquad \varsigma \equiv \big[f_E(\rho-1)\big]^{-1/(\rho-1)}. \tag{30}$$

Manufacturing output exhibits increasing returns ($1+\vartheta > 1$) in production labor, amplified by a lower effective entry wedge. Expanding $\tau_{r,t}^{\text{eff}}$ via (22), the increasing returns trace to three primitives: love of variety ($\vartheta > 0$), network entry cost ($\Pi(A)$ increasing in the supplier base), and ecosystem persistence ($\eta < 1$).

10.7 Sectoral Labor Supply: Roy Model with Fréchet Skills

Each type $\nu \in \{I, F\}$ draws sector-specific skill z_s independently from a Fréchet distribution:

$$\Pr(z_s \leq z) = \exp\Big(-\phi_s^\nu \, z^{-\theta}\Big), \qquad z > 0, \ \theta > 1. \tag{31}$$

Here $\phi_s^\nu > 0$ is the scale parameter governing the central tendency of type-ν draws in sector s, and θ is the shape parameter governing dispersion. We assume type I has a comparative advantage in manufacturing: $\phi_M^I/\phi_A^I > \phi_M^F/\phi_A^F$.

An individual of type ν in region r with draws (z_A, z_M) earns $w_{rs,t} \cdot z_s$ in sector s and chooses the sector offering higher earnings. The standard Fréchet result gives the probability of choosing sector s:

$$\pi_{rs,t}^\nu = \frac{\phi_s^\nu \, w_{rs,t}^\theta}{\phi_A^\nu \, w_{rA,t}^\theta + \phi_M^\nu \, w_{rM,t}^\theta}. \tag{32}$$

Define the type-ν expected wage index:

$$\bar{w}_{r,t}^\nu \equiv \big(\phi_A^\nu \, w_{rA,t}^\theta + \phi_M^\nu \, w_{rM,t}^\theta\big)^{1/\theta}. \tag{33}$$

The sectoral share can be written compactly as $\pi_{rs,t}^\nu = \phi_s^\nu \, (w_{rs,t}/\bar{w}_{r,t}^\nu)^\theta$.

By allowing for the latent types I and F, the model provides a distinct role for the composition of the local population to determine labor supply. Total manufacturing labor supply in efficiency units is:

$$H_{rM,t} = \Gamma\!\left(1 - \frac{1}{\theta}\right) \sum_{\nu \in \{I,F\}} L_{r,t}^\nu \, (\phi_M^\nu)^{1/\theta} \, (\pi_{rM,t}^\nu)^{(\theta-1)/\theta}. \tag{34}$$

10.8 Spatial Mobility

Individuals are mobile across space but mobility is subject to frictions. Amenities in location r are a power function of the local population, reflecting congestion:

$$\mathcal{B}_{r,t} = \mathcal{B}_r \, L_{r,t}^{-\beta}, \qquad \beta \geq 0, \tag{35}$$

where $\mathcal{B}_r > 0$ is a location-specific amenity fundamental and β is the congestion elasticity.

Individuals know their type before making moving decisions but do not observe their particular skill realization z_{it}. Each individual draws an i.i.d. location preference shock ζ_r from a Fréchet distribution with shape parameter $\varepsilon > 1$. Moving from origin j to destination r incurs a multiplicative utility cost $\kappa_{jr} \in (0, 1]$. The expected utility for an individual of type ν currently in j who moves to r is $V_{jr}^\nu = \mathcal{B}_{r,t} \, \kappa_{jr} \, \tilde{u}_{r,t}^\nu \, \zeta_r$, where $\tilde{u}_{r,t}^\nu \equiv \bar{w}_{r,t}^\nu / P_{r,t}$ is type-ν expected real income and $P_{r,t} \equiv P_{rA,t}^\alpha \, P_{rM,t}^{1-\alpha}$ is the Cobb–Douglas price index.

The share of type-ν individuals moving from j to r is given by the gravity equation:

$$m_{jrt}^{\nu} = \frac{\left(\mathcal{B}_{r,t}\,\kappa_{jr}\,\tilde{u}_{r,t}^{\nu}\right)^{\varepsilon}}{\sum_{d=1}^{R}\left(\mathcal{B}_{d,t}\,\kappa_{jd}\,\tilde{u}_{d,t}^{\nu}\right)^{\varepsilon}}. \tag{36}$$

Equation (36) encapsulates the economics of spatial sorting: because industrial types put a higher weight on manufacturing wages via their expected earnings $\bar{w}_{r,t}^{I}$, they move toward locations with a comparative advantage in manufacturing.

Only a fraction $\psi \in (0,1]$ of individuals reoptimizes location each period. The law of motion for the type-ν population in region r is:

$$L_{r,t}^{\nu} = (1-\psi)\,L_{r,t-1}^{\nu} + \psi \sum_{j=1}^{R} L_{j,t-1}^{\nu}\,m_{jrt}^{\nu}. \tag{37}$$

The Calvo shock ψ governs the persistence of the initial population distribution; the bilateral frictions κ_{jr} govern the spatial proximity of moving flows.

10.9 Equilibrium

10.9.1 Static Equilibrium

Definition 1 (Static equilibrium)**.** Given $\{Q_{r,t}, N_{r,t-1}, A_{r,t-1}, L_{r,t}^{\nu}\}_{r,\nu}$ and $\{\tau_{r,t}^{\text{exog}}\}_r$, a static equilibrium is a set of wages and land rents $\{w_{rA,t}, w_{rM,t}, R_{r,t}\}_r$, intermediate varieties, input prices and quantities $\{N_{r,t}, [p_{r,t}(i), x_{r,t}(i)]_i\}_r$, sectoral employment allocations $\{H_{rA,t}, H_{rP,t}, H_{rE,t}\}_r$, and quantities of tradable goods $\{Y_{rA,t}, Y_{rM,t}\}_r$, such that (i) firms and consumers behave optimally and (ii) labor and goods markets clear.

Given the aggregate sectoral production functions in (13) and (30), the static equilibrium can be fully characterized given the vector of $(Q_{r,t}, N_{r,t-1}, A_{r,t-1})$ and the population distribution $L_{r,t} = (L_{r,t}^{F}, L_{r,t}^{I})$.

The equilibrium size of the manufacturing production workforce ("market size") is given by

$$H_{rP,t}\big(\{Q_{r,t}, N_{r,t-1}, A_{r,t}, L_{r,t}^{\nu}\}\big) = \frac{\rho-1}{\rho}\left[\Gamma\left(1-\frac{1}{\theta}\right)\sum_{\nu\in\{I,F\}} L_{r,t}^{\nu}\,\phi_{M}^{\nu}\,\frac{w_{rM,t}^{\theta-1}}{(\bar{w}_{r,t}^{\nu})^{\theta-1}} + (1-\delta)\,f_{E}\,\tau_{r,t}^{\text{eff}}\,N_{r,t-1}\right]. \tag{38}$$

This highlights that local market size depends on both the size and composition of the population and on the local manufacturing share determined in the trade equilibrium.

10.9.2 Dynamic Equilibrium

Definition 2 (Dynamic equilibrium)**.** Given a path of exogenous productivity $\{Q_{r,t}\}_{r,t}$, exogenous policy $\{\tau_{r,t}^{\text{exog}}\}_{r,t}$, and initial conditions $\{L_{r,0}^{\nu}, N_{r,0}, A_{r,0}\}_{r,\nu}$, a dynamic equilibrium is a path of local populations $\{L_{r,t}^{\nu}\}_{r,\nu,t}$, local varieties $\{N_{r,t}\}_{r,t}$, and ecosystem stocks $\{A_{r,t}\}_{r,t}$ such that: (i) $\{L_{r,t}^{\nu}\}$ is consistent with individuals' optimal mobility decisions; (ii) $\{N_{r,t}\}$ is consistent with free entry; (iii) $\{A_{r,t}\}$ evolves according to the ecosystem law of motion; (iv) the resulting allocations represent a static equilibrium at each point in time.

The laws of motion of the three endogenous state variables are:

$$N_{r,t} = \frac{1}{f_E(\rho-1)\,\tau_{r,t}^{\text{exog}}} \times H_{rP,t}\big(\{Q_{r,t}, N_{r,t-1}, A_{r,t}, L_{r,t}^{\nu}\}\big) \times \Pi(A_{r,t}), \tag{39}$$

$$A_{r,t} = (1-\eta)\,A_{r,t-1} + \eta\,N_{r,t-1}, \tag{40}$$

$$L_{r,t}^{\nu} = (1-\psi)\,L_{r,t-1}^{\nu} + \psi \sum_{j=1}^{R} L_{j,t-1}^{\nu}\, m_{jrt}^{\nu}\big(\{Q_{r,t}, N_{r,t-1}, A_{r,t}, L_{r,t}^{\nu}\}\big)\,. \tag{41}$$

These describe the joint evolution of local productivity, the local ecosystem, and the local population. $N_{r,t}$ depends on $L_{r,t}^{\nu}$ through market size and on $A_{r,t}$ through $\Pi(\cdot)$; $L_{r,t}^{\nu}$ depends on varieties through equilibrium wages and migration; $A_{r,t}$ depends on past $N_{r,t-1}$, providing the slow-moving channel through which history shapes entry conditions.

10.10 Population Inflows and Persistent Local Productivity Dynamics

Taking logs of (39):

$$\ln N_{r,t} = \alpha_0 + \ln H_{rP,t} + \ln \Pi(A_{r,t}) - \ln \tau_{r,t}^{\text{exog}}, \tag{42}$$

where $\alpha_0 = \ln(1/[f_E(\rho-1)])$.

Regime-dependent persistence. The effective persistence of the productivity process depends on the region's position relative to A^*. Near A^*, small changes in A produce large changes in $\Pi(A)$, generating strong positive feedback. Far from A^*, $\Pi(A)$ is nearly flat and the feedback is weak. Thus, the model endogenously generates heterogeneous persistence across regions depending on their ecosystem development.

Critical-mass thresholds. A region below critical mass ($A_r < A^*$) faces prohibitively high entry costs, sustaining a poverty trap even with moderate population inflows. A region above critical mass ($A_r > A^*$) enjoys low entry costs and converges to the industrialized equilibrium.

History dependence. Because $A_{r,t}$ is an exponentially weighted moving average of all past variety counts (24), the productivity process depends on the entire history of local firm activity:

$$\ln N_{r,\tau} = \alpha_0 + \ln H_{rP,\tau} + \ln \Pi \left(\eta \sum_{k=0}^{\infty} (1-\eta)^k N_{r,\tau-1-k} \right) - \ln \tau_{r,\tau}^{\text{exog}}. \tag{43}$$

10.11 Parameter Summary

10.12 Estimating the Model

under construction

11 Aggregate Effects:

under construction

12 Conclusion

This paper investigates whether a temporary burst of government procurement can permanently alter the economic trajectory of a region. I exploit quasi-random variation in the placement of Quartermaster facilities during the U.S. Civil War and trace the evolution of affected counties from 1820 to 2000. Comparing treated counties to others with similar 1860 levels of population, infrastructure, and manufacturing capacity, I find that wartime procurement had large and persistent effects on local development: treated counties experienced sustained gains in population, manufacturing employment, firm entry, and county revenue that persisted for over a century after procurement ended. These persistent effects without persistent spending constitute direct evidence for path dependence operating through the supply-side network formation channel emphasized by Hirschman, 1958 and formalized in the model, once the procurement shock pushed the local supplier base past a critical mass threshold, the self-reinforcing dynamics of the network externality sustained industrialization without further government intervention.

The effects extended beyond aggregate county-level outcomes. Wartime procurement triggered a durable structural transformation: manufacturing's share of local output rose significantly while agricultural output showed no comparable response, and growth operated on the extensive margin, more firms and greater product variety rather than larger plants. Treated counties also experienced sustained gains in technical and industrial patenting, consistent with the model's prediction that a thicker supplier base raises not only output but also innovative activity through horizontal variety expansion. At the individual level, men who grew up in treated counties achieved significant upward occupational mobility, with the largest gains concentrated among those from the most

disadvantaged households. These mobility gains were fundamentally tied to place rather than portable: they disappeared after conditioning on 1880 location and were absent among movers, confirming that the mechanism operates through local economic opportunities sustained by the supplier network.

The nature of the intervention matters critically for persistence. Both Quartermaster and Ordnance sites experienced short-run improvements during the war, but only QM sites, where procurement was broad-based and generated substantial firm entry across diversified industries, exhibited long-run effects. Ordnance sites, which involved narrow, specialized production that created few new establishments and limited supplier linkages, showed no lasting impact. This contrast provides a within-setting test of the model's core prediction: it is the breadth and diversity of the initial entry wave, and the resulting thickness of the local supplier network, that determines whether a temporary shock becomes self-sustaining.

The Civil War occurred as the United States was transitioning from an agrarian to an industrial economy, and the procurement shock accelerated this transition in treated counties. An important question for future research is whether similar interventions could help developing economies today. The contemporary landscape differs in ways that may attenuate the mechanism documented here: automation reduces the labor intensity of manufacturing, potentially weakening the population-attraction channel; and the rise of large service-sector firms may offer an alternative path to agglomeration, though one with weaker inter-firm supply linkages and greater skill-matching frictions at the point of initial entry. Understanding whether and how the supply-side Big Push logic translates to modern economic structures remains an open and consequential question for industrial policy.

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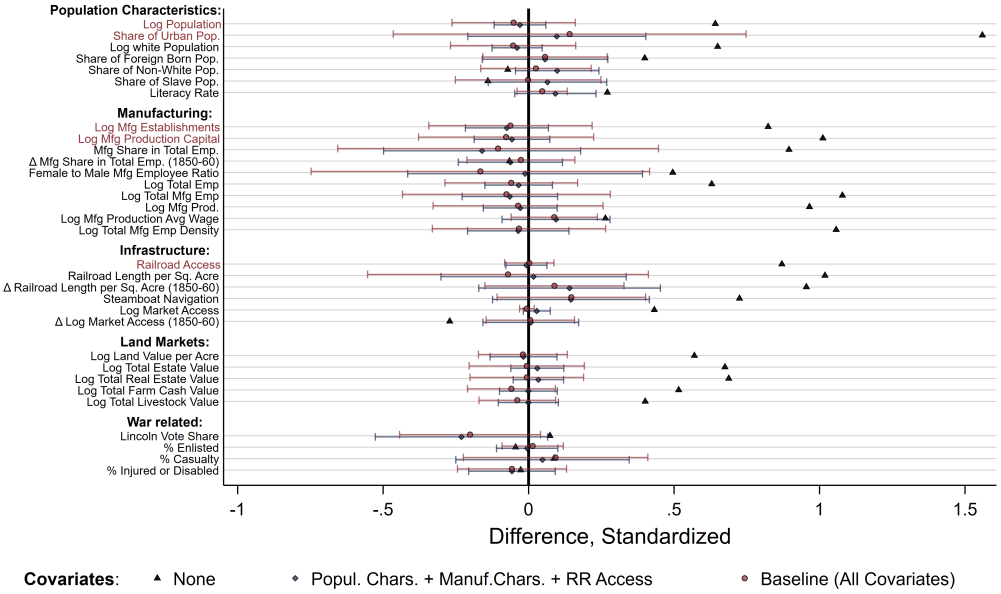
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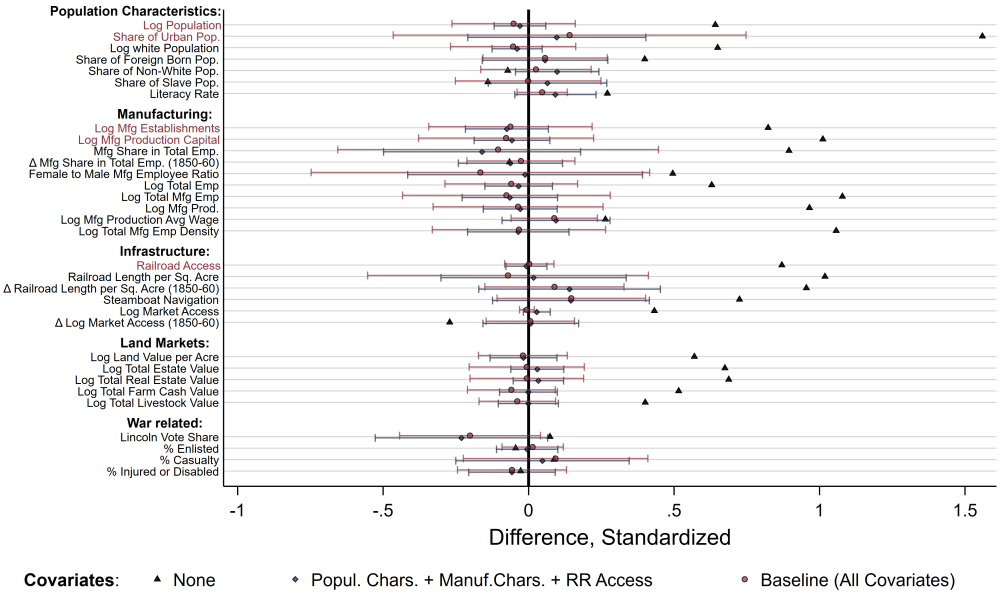
Figures

Figure 8: County-Level Covariate Balance

(a) OLS



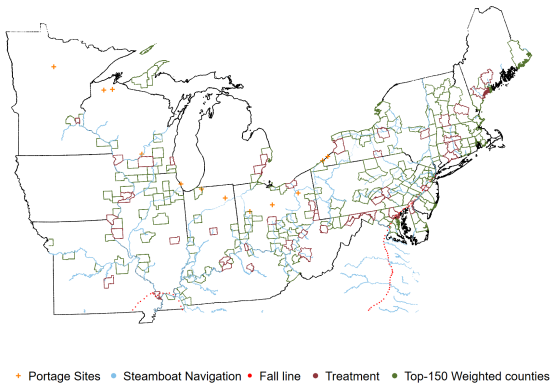
(b) Reweighted Differences



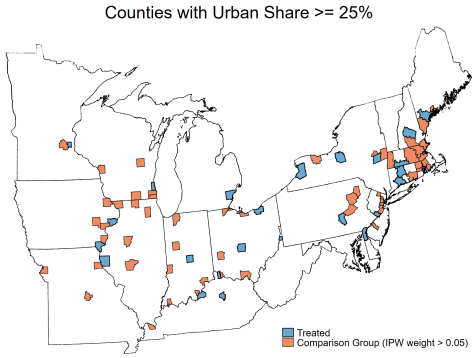
Notes: Figure 8a displays estimates of raw and propensity-score-reweighted differences (from Equation 6) between treated and comparison counties for pre-war county characteristics, using alternative sets of covariates. Figure 8b displays estimates from OLS regressions of pre-war county characteristics on the main treatment indicator following the specification in Equation 1 using alternative sets of covariates.

Figure 9: Counterfactual County features

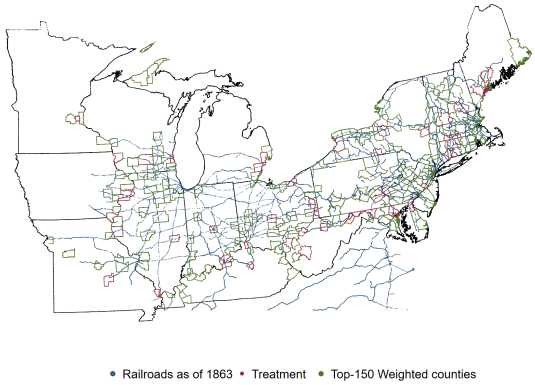
(a) Portage and Navigation



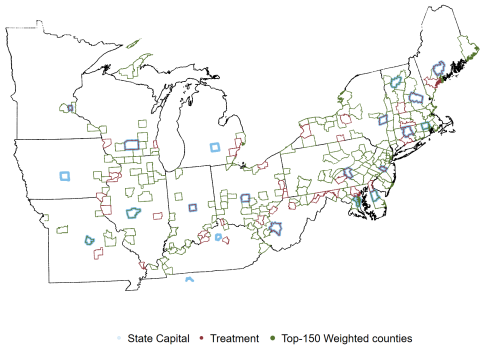
(b) Urbanization



(c) Railroads



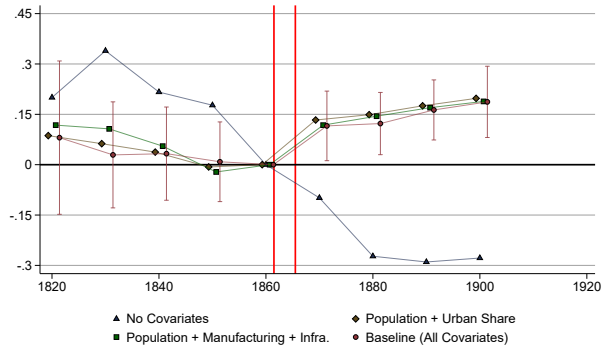
(d) State Capitals



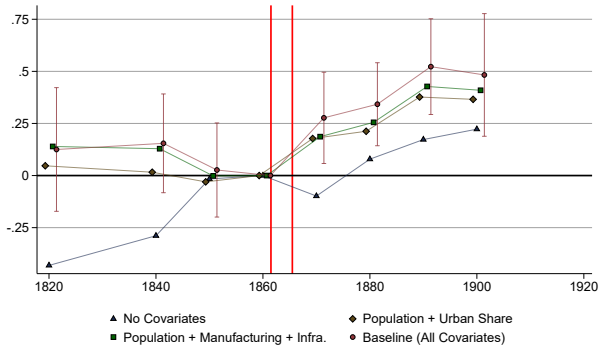
Notes: Figure displays OLS estimates of levels regression rather than differences. Each estimate and the associated 95% confidence interval is from a separate regression of the outcome measured in the year specified in the x-axis on the treatment indicator. Outcomes are county-level tabulations from the Decennial Censuses or the Census of Manufactures.

Figure 10: Identification

(a) Log Population (OLS)



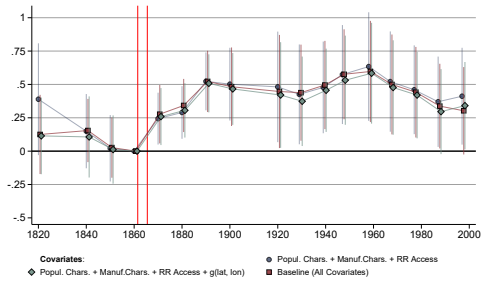
(b) Log Mnf Production Employment (OLS)



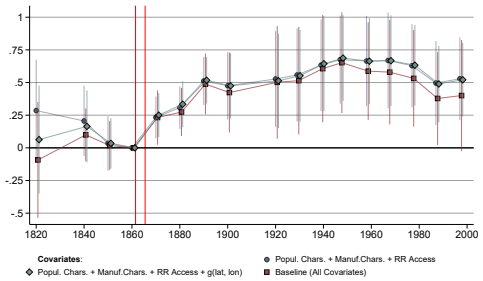
Notes: Figure displays OLS estimates of Equation 1 under alternative covariate specifications described in the main text. Each estimate and the associated 95% confidence interval is from a separate regression of the outcome measured in the year specified in the x-axis on the treatment indicator. Outcomes are county-level tabulations from the Decennial Censuses or the Census of Manufactures. 1860 estimates are mechanically zero. Red lines denote beginning and end of U.S. Civil War.

Figure 11: County-Level Dynamics

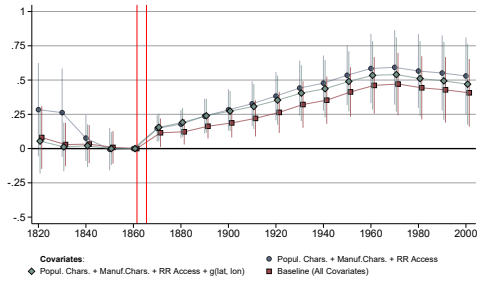
(a) Log Mnf Production Employment (OLS)



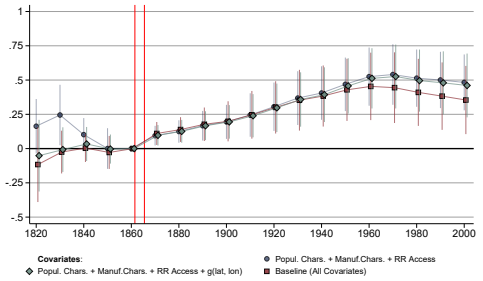
(b) Log Mnf Production Employment (IPW)



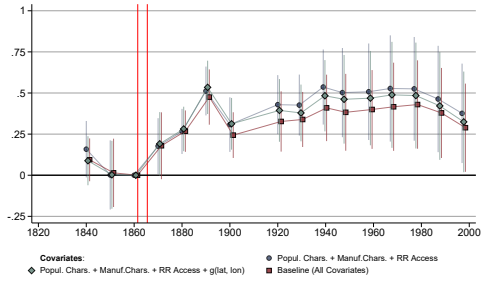
(c) Log Population (OLS)



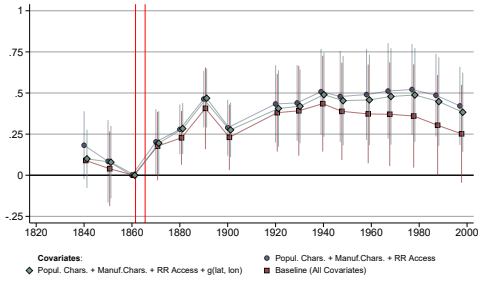
(d) Log Population (IPW)



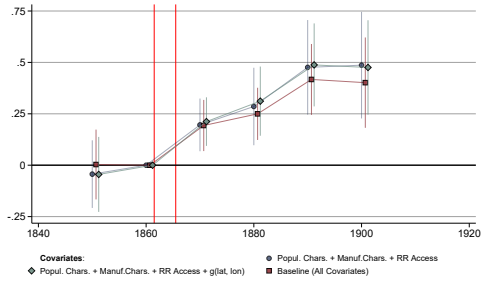
(e) Log Mnf Establishments (OLS)



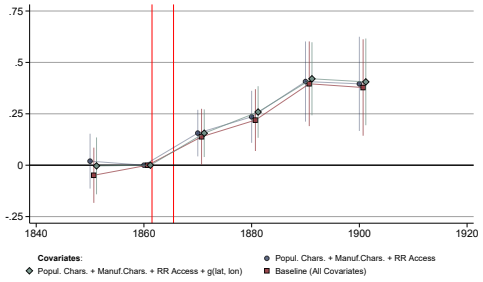
(f) Log Mnf Establishments (IPW)



(g) Log Total County Revenue (OLS)



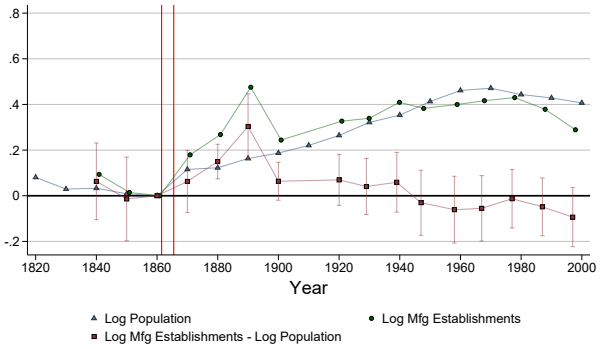
(h) Log Total County Revenue (IPW)



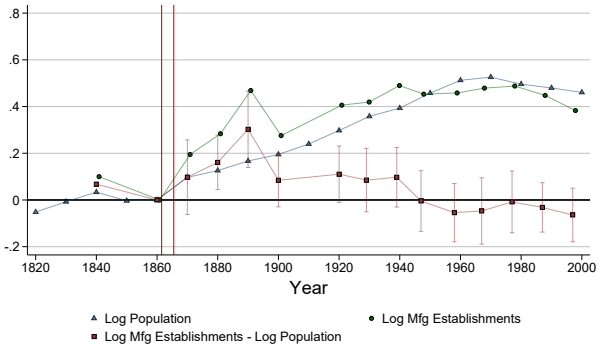
Notes: Figure displays OLS and IPW estimates of Equation 1 and Equation 6 respectively, under alternative covariate specifications. Each estimate and the associated 95% confidence interval is from a separate regression of the outcome measured in the year specified in the x-axis on the treatment indicator. Outcomes are county-level tabulations from the Decennial Censuses or the Census of Manufactures. 1860 estimates are mechanically zero. Red lines denote beginning and end of U.S. Civil War.

Figure 12: County-Level Dynamics

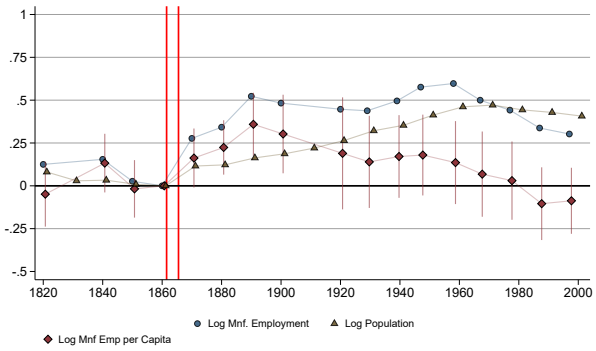
(a) Population vs Mfg Establishment (OLS)



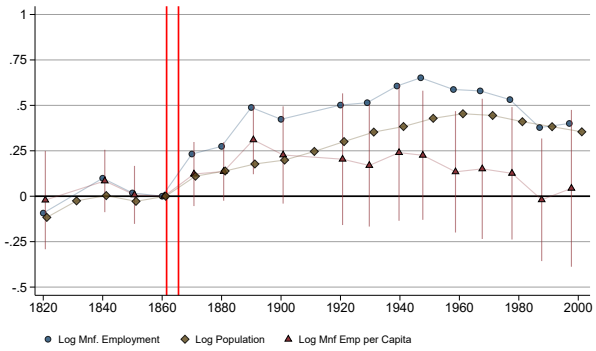
(b) Population vs Mfg Establishment (IPW)



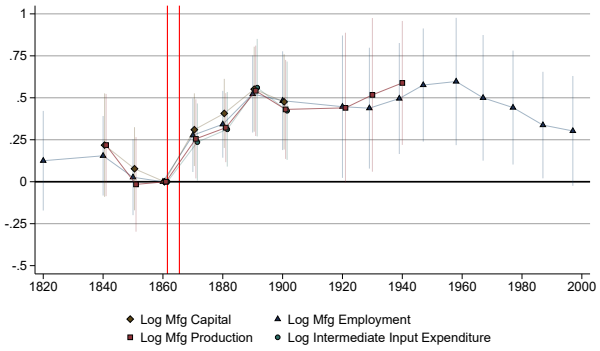
(c) Employment vs Population Dynamics (OLS)



(d) Employment vs Population Dynamics (IPW)



(e) Production, Capital, Employment (OLS)



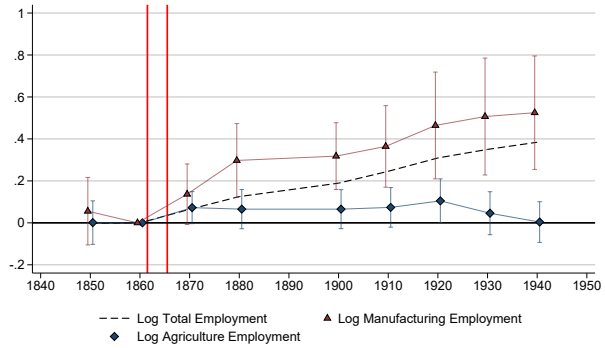
(f) Production, Capital, Employment (IPW)



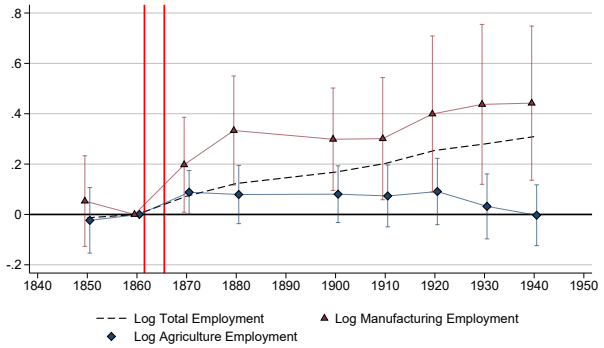
Notes: Figure displays OLS and IPW estimates of Equation 1 and Equation 6 respectively. Each estimate and the associated 95% confidence interval is from a separate regression of the outcome measured in the year specified in the x-axis on the treatment indicator. Outcomes are county-level tabulations from the Decennial Censuses or the Census of Manufactures. 1860 estimates are mechanically zero. Red lines denote beginning and end of U.S. Civil War. All specifications use baseline covariate set.

Figure 13: County-Level Dynamics: Employment by Sector (Based on County of Residence)

(a) *Including Adjoining Counties*



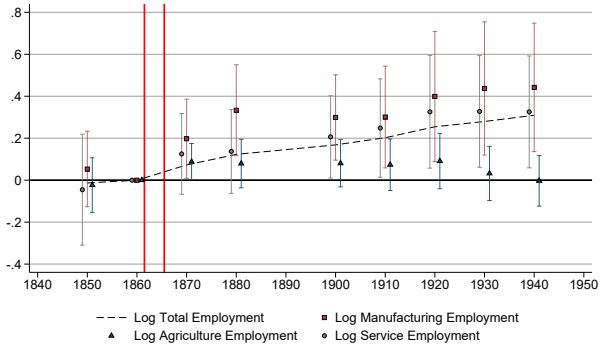
(b) *Excluding Adjoining Counties*



(c) *Including Adjoining Counties*



(d) *Excluding Adjoining Counties*



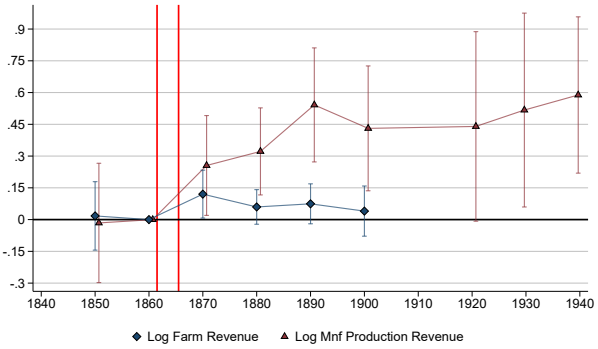
Notes: Figure displays OLS estimates of Equation 1. Each estimate and the associated 95% confidence interval is from a separate regression of the outcome measured in the year specified in the x-axis on the treatment indicator. Outcomes are county-level tabulations from the Decennial Censuses or the Census of Manufactures. 1860 estimates are mechanically zero. Red lines denote beginning and end of U.S. Civil War. All specifications use baseline covariates.

Table 1: Employment Shares (by county of residence)

	Manufacturing (1880)	Agriculture (1880)	Services (1880)
		Shares	
QM	0.015**	-0.021	0.006
	(0.007)	(0.014)	(0.015)
		Log Shares	
QM	0.212***	-0.044	0.016
	(0.073)	(0.042)	(0.058)
N	823	823	823

Figure 14: Income Dynamics

(a) Output by Sector



(b) Income per Employee



Notes: Figure displays estimates of Equation 1. Each estimate and the associated 95% confidence interval is from a separate regression of the outcome measured in the year specified in the x-axis on the treatment indicator. Outcomes are county-level tabulations from the Decennial Censuses or the Census of Manufactures. 1860 estimates are mechanically zero. Red lines denote beginning and end of U.S. Civil War. All specifications use extended covariate set.

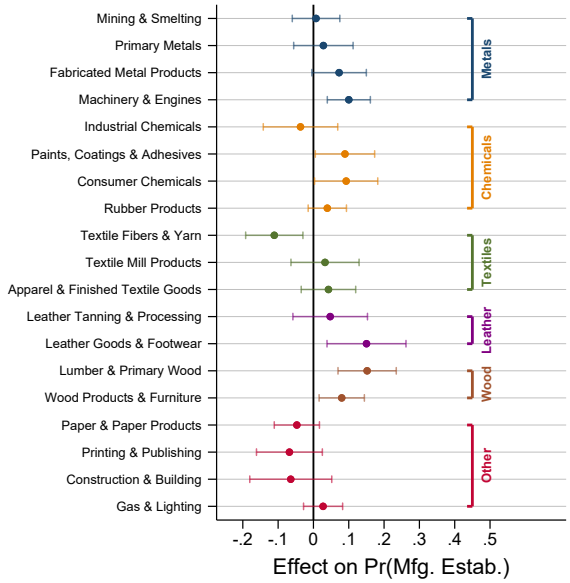
Table 2: Structural Change

			Log Average Establishment Size		Mfg. Share of County		
	Log Number of Industries (1880)	Log Number of Establishments	Revenue per Establishment	Workers per Establishment	Revenue	Value Added	Income per Employee
QM	0.213***	0.475***	0.089	0.107	0.072**	0.058*	0.143***
	(0.071)	(0.086)	(0.075)	(0.099)	(0.026)	(0.028)	(0.044)
Observations	1011	1009	999	999	995	999	1011

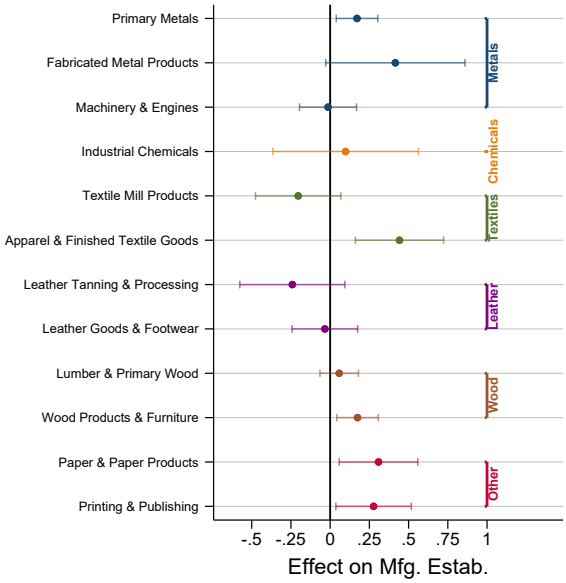
Standard errors in parentheses

Figure 15: Industry Creation

(a) Extensive Margin



(b) Intensive Margin



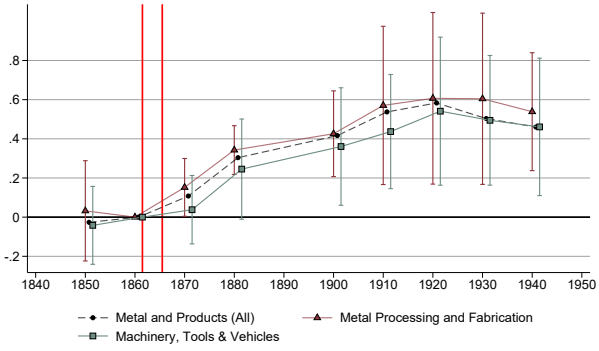
Notes: Panel (a) reports the effect of treatment on the probability that a given industry is present in the county (extensive margin). Panel (b) reports the effect on the number of manufacturing establishments conditional on industry presence (intensive margin). Each estimate and the associated 95% confidence interval is from a separate regression. All specifications use baseline covariates.

Figure 16: Industry Dynamics

(a) Clothing & Metal Industries



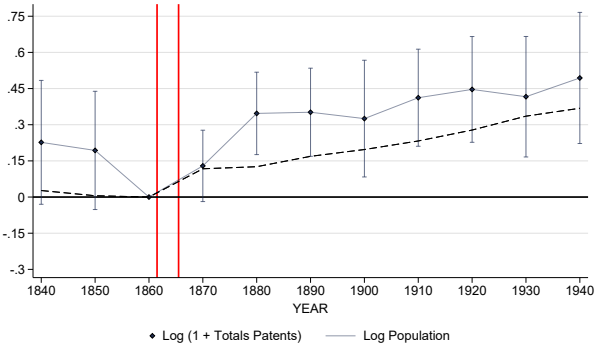
(b) Decomposition of Metal Industry Employment



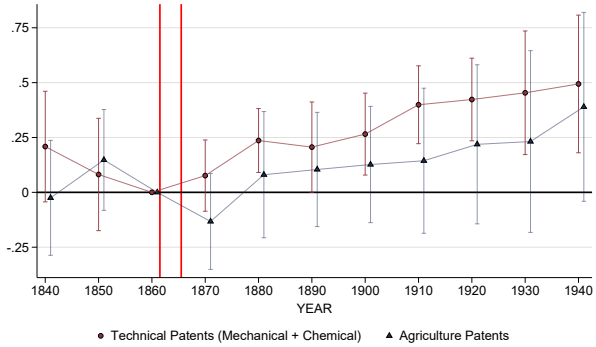
Notes: Figure displays OLS estimates of Equation 1. Each estimate and the associated 95% confidence interval is from a separate regression of the outcome measured in the year specified in the x-axis on the treatment indicator. Red lines denote beginning and end of U.S. Civil War. All specifications use baseline covariates.

Figure 17: Effect on Innovation

(a) Log (1 + Total Patents)



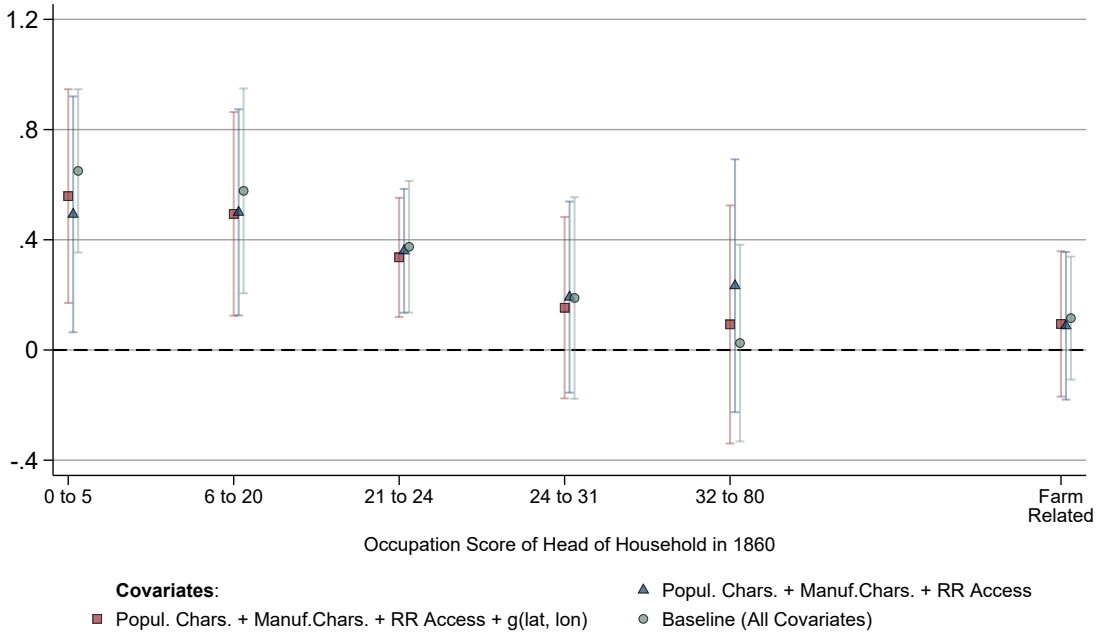
(b) Log (1 + Technical Patents)



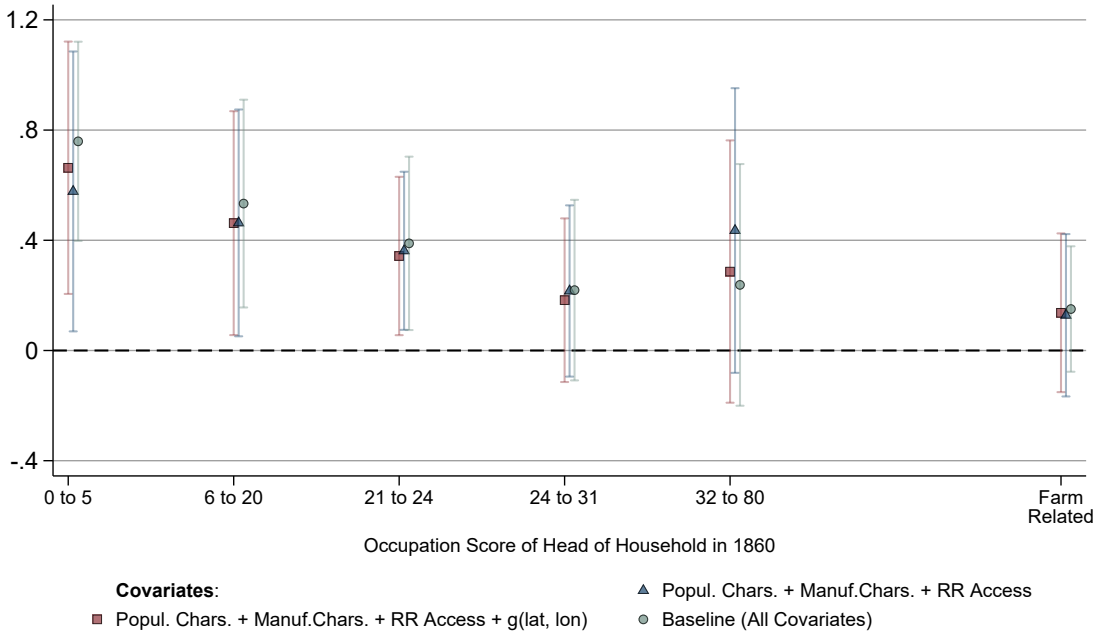
Notes: Figure displays OLS estimates of levels regression rather than differences. Each estimate and the associated 95% confidence interval is from a separate regression of the outcome measured in the year specified in the x-axis on the treatment indicator. Outcomes are county-level tabulations from the Decennial Censuses or the Census of Manufactures.

Figure 18: Effects on Occupational Mobility

(a) Age: 21–37 (in 1880)



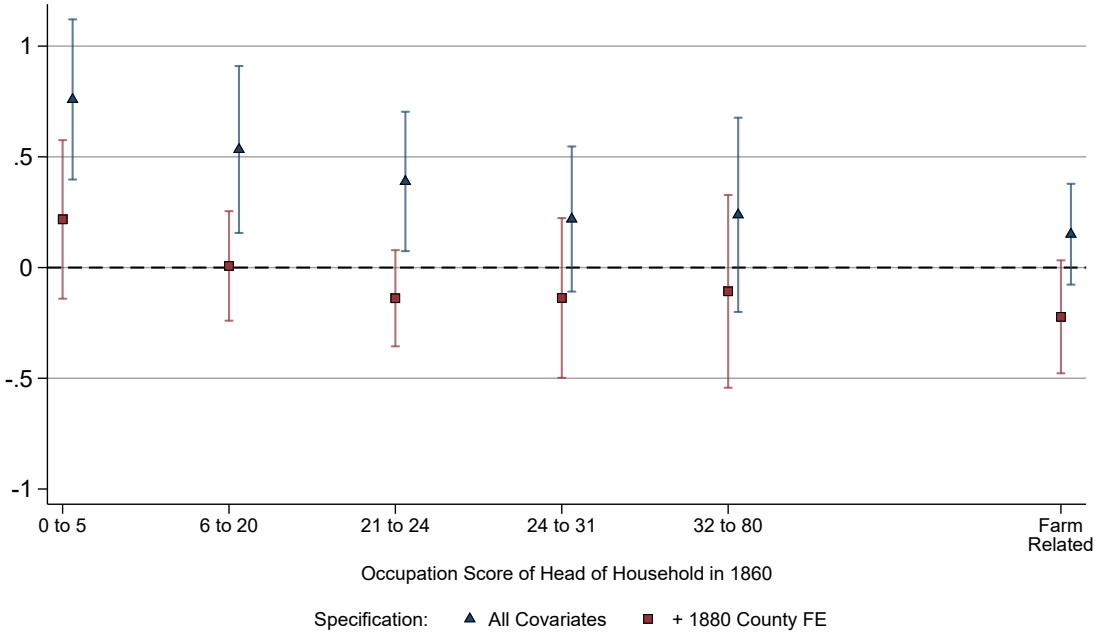
(b) Age: 21–30 (in 1880)



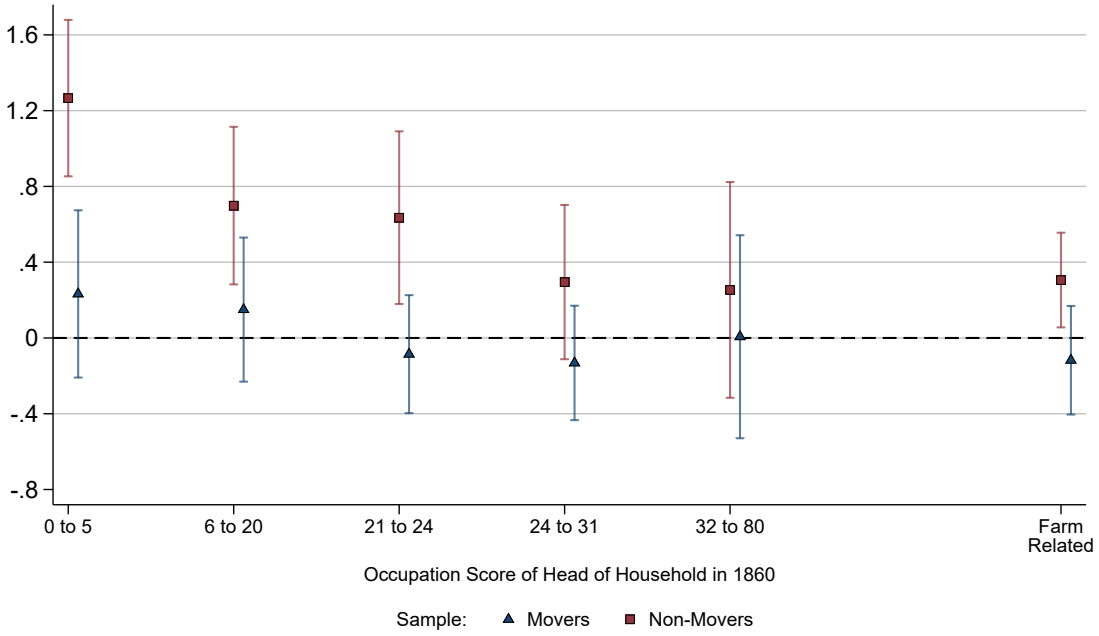
Notes: Figure displays estimates of Equation 7 under alternative covariate specifications. The sample comprises all white men born between 1842–1860 or 1850–1860 in one of the 47 treatment or 1,001 comparison counties who are matched to their household in the 1860 Census. Each estimate and the associated 95% confidence interval is from a separate regression; standard errors are clustered at the state level.

Figure 19: People versus Place Age: 21–31 (in 1880)

(a) 1880 Location FE



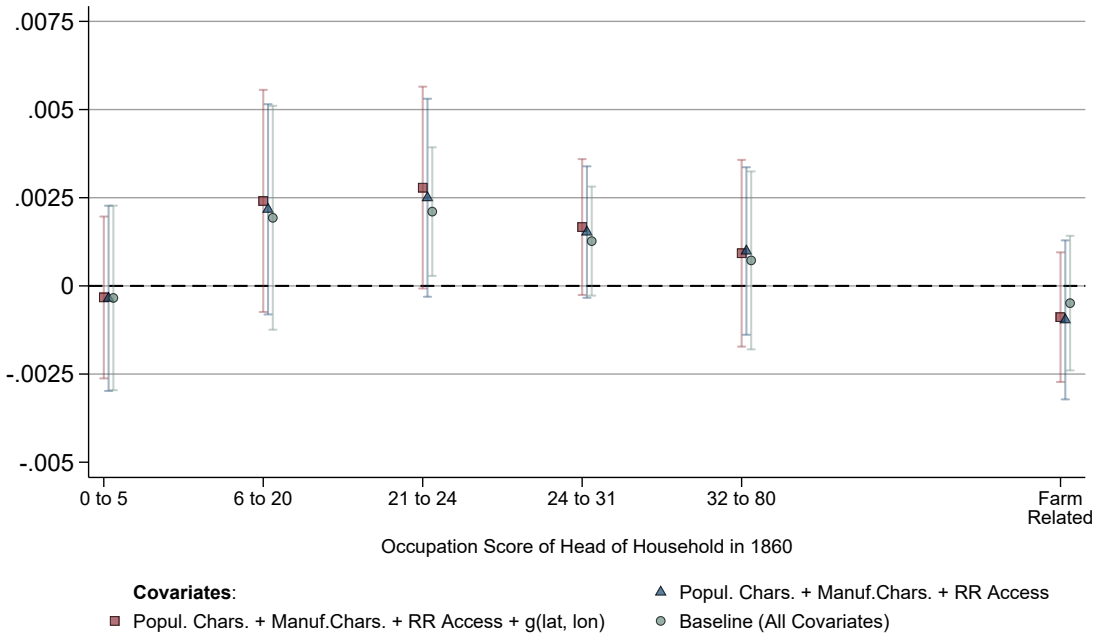
(b) Movers versus Non-Movers



Notes: Figure displays estimates of Equation 7 under alternative specifications. The sample comprises all white men born between 1850–1860 in one of the 47 treatment or 1,001 comparison counties who are matched to their household in the 1860 Census. Each estimate and the associated 95% confidence interval is from a separate regression; standard errors are clustered at the state level.

Figure 20: Effects on Literacy

Age: 21-30 (in 1880)



Notes: Figure displays estimates of Equation 8, using literacy indicator as the outcome. Under alternative covariate specifications. The sample is all men between 1850–1860 in one of the 47 treatment or 1001 comparison counties who are matched to their household in the 1860 Census. Each estimate and the associated 95% confidence interval is from a separate regression, where standard errors are clustered at the state level

Tables

Table 3: County-Level:Heterogeneity

(a) 1860 Economy Features

	Log Total Mfg Emp. (1890)				Log Total Population (1890)			
QM (Main Effect)	0.523***	0.993***	0.632***	0.698**	0.163***	0.344***	0.179***	0.185**
	(0.117)	(0.281)	(0.184)	(0.263)	(0.046)	(0.099)	(0.063)	(0.083)
QM x Log(Population - 1860)		-0.613**				-0.236**		
		(0.266)				(0.108)		
QM x Manf. Share(1860)			-0.129				-0.016	
			(0.132)				(0.049)	
QM x Emp. Density (1860)				-0.180				-0.022
				(0.181)				(0.067)
Observations	999	999	995	999	1011	1011	1007	1011
All Covariates	✓	✓	✓	✓	✓	✓	✓	✓

(b) Robustness to Railroads

	Log Total Mfg Emp. (1890)							Log Total Population (1890)						
QM (Main Effect)	0.508***	0.508***	0.485**	0.614***	0.446***	0.480***	0.451**	0.240***	0.237***	0.181***	0.215**	0.158**	0.168*	0.209***
	(0.111)	(0.112)	(0.205)	(0.189)	(0.080)	(0.122)	(0.172)	(0.063)	(0.061)	(0.061)	(0.078)	(0.057)	(0.079)	(0.061)
QM x Δ Market Access (1830-1860)		-0.015							-0.039					
		(0.144)							(0.065)					
QM x Railroad Density (1860)			0.008							0.047				
			(0.128)							(0.054)				
QM x Railroad Length (1860)				-0.114							-0.006			
				(0.092)							(0.040)			
Observations	999	999	999	999	488	188	811	1011	1011	1011	1011	488	188	823
All Covariates	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sample Restriction:														
Counties with Railroad access					✓							✓		
Log market Access (1860) ≥ Median						✓							✓	
Log market Access (1860) < Median							✓							✓

The table presents OLS estimates of Equation 1.

Table 4: Other County Features

	Log Total Mfg Emp. (1890)					Log Total Population (1890)				
QM (Main Effect)	0.523***	0.533***	0.530***	0.581***	0.517***	0.163***	0.174***	0.114*	0.184***	0.114**
	(0.117)	(0.129)	(0.138)	(0.129)	(0.141)	(0.046)	(0.050)	(0.063)	(0.052)	(0.052)
QM x Great Lake County		-0.095					-0.103			
		(0.226)					(0.135)			
QM x State Capital			-0.509					0.088		
			(0.438)					(0.226)		
QM x Armory				-0.135					-0.048	
				(0.232)					(0.119)	
Observations	999	999	999	999	522	1011	1011	1011	1011	527
All Covariates	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sample Restriction:										
Steamboat Navigable					✓					✓

The table presents OLS estimates of Equation 1.

A Appendix

Table A.5: QM Sites included Estimation Sample

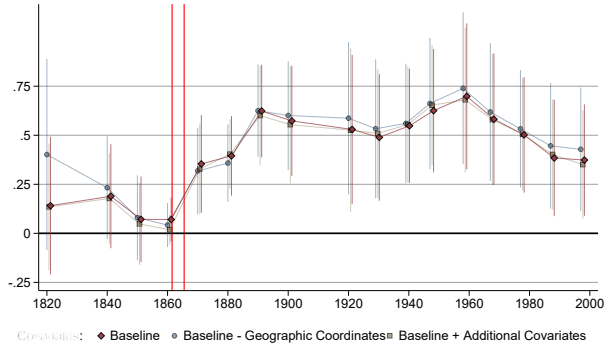
S No.	State	County
1	Connecticut	Hartford
2	Connecticut	New Haven
3	Delaware	New Castle
4	Illinois	Adams
5	Illinois	Alexander
6	Illinois	Coles
7	Illinois	Rock Island
8	Indiana	Clark
9	Indiana	Marion
10	Iowa	Lee
11	Iowa	Scott
12	Kentucky	Fayette
13	Kentucky	Jefferson
14	Kentucky	Kenton
15	Maine	Cumberland
16	Maine	Kennebec
17	Maryland	Allegany
18	Maryland	Baltimore County
19	Maryland	Washington
20	Massachusetts	Hampden
21	Michigan	Macomb
22	Michigan	Wayne
23	Minnesota	Hennepin
24	Minnesota	Ramsey
25	Missouri	Phelps
26	New Hampshire	Merrimack
27	New Jersey	Mercer
28	New York	Albany
29	New York	Chemung
30	New York	Erie
31	New York	Onondaga
32	Ohio	Cuyahoga
33	Ohio	Franklin
34	Ohio	Gallia
35	Ohio	Jefferson
36	Pennsylvania	Cumberland
37	Pennsylvania	Dauphin
38	Vermont	Windham
39	West Virginia	Harrison
40	West Virginia	Kanawha
41	West Virginia	Marshall
42	West Virginia	Mineral
43	West Virginia	Ohio
44	West Virginia	Wood
45	Wisconsin	Crawford
46	Wisconsin	Dane
47	Wisconsin	Milwaukee

Table A.6: Ordnance Sites included Estimation Sample

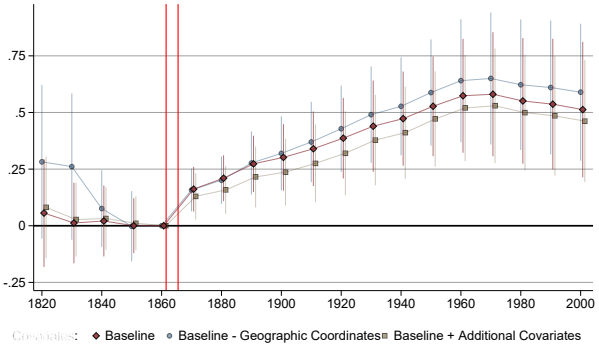
S No.	State	County
1	Illinois	Rock Island
2	Maine	Kennebec
3	Maryland	Baltimore
4	Massachusetts	Hampden
5	Massachusetts	Middlesex
6	Michigan	Macomb
7	Michigan	Wayne
8	Missouri	Pike
9	New York	Albany
10	New York	Putnam
12	Ohio	Franklin
13	Vermont	Addison
14	West Virginia	Jefferson

Figure A.21: Outcome Level Effect

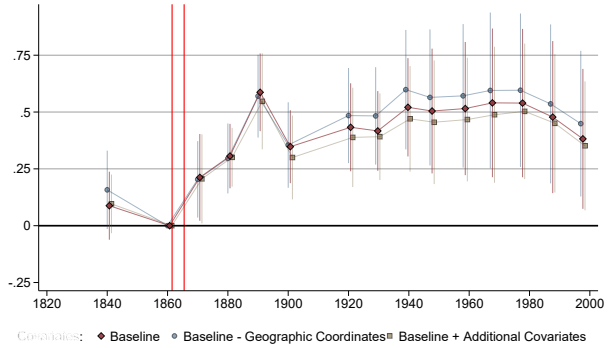
(a) Log Mnf Production Employment



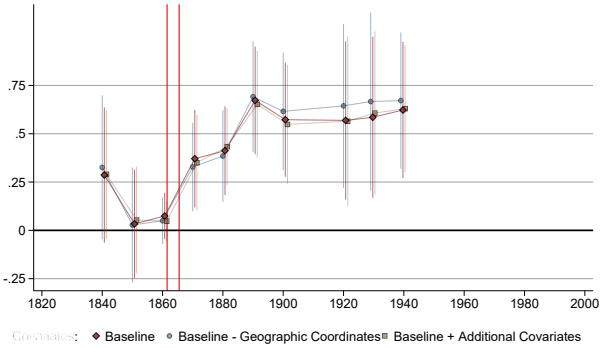
(b) Log Population



(c) Log Mnf Establishments



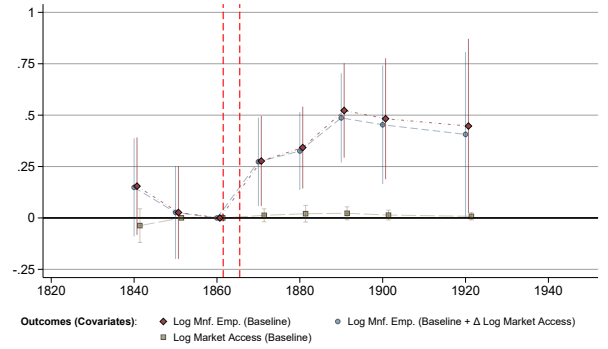
(d) Log Manufacturing Production



Notes: Figure displays OLS estimates of levels regression rather than differences. Each estimate and the associated 95% confidence interval is from a separate regression of the outcome measured in the year specified in the x-axis on the treatment indicator. Outcomes are county-level tabulations from the Decennial Censuses or the Census of Manufactures.

Figure A.22: Robustness: Market Access

(a) Log Mnf Production Employment



(b) Log Population

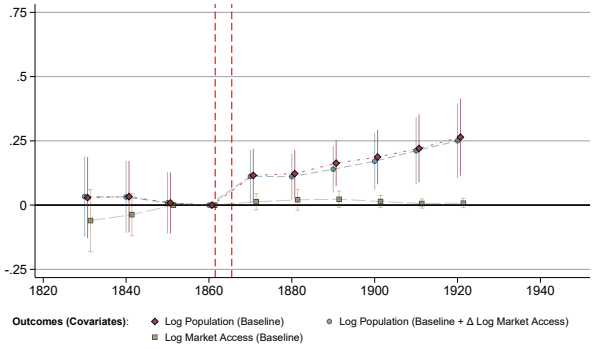
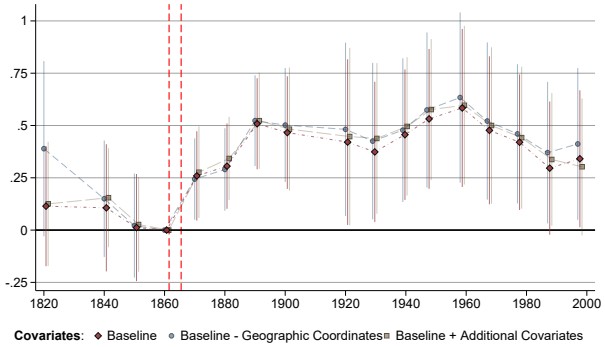


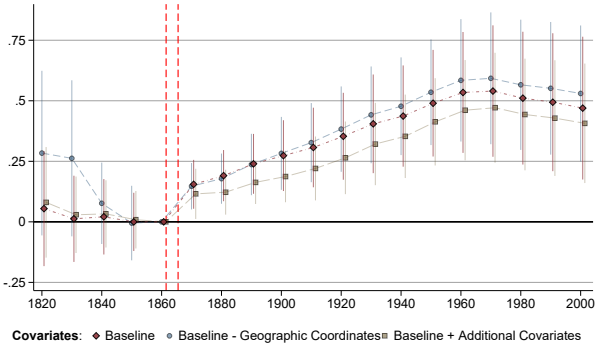
Figure displays OLS estimates of Equation 1 and equation $Y_c - Y_{c,1860} = \alpha + \boldsymbol{\tau}.d_c + \lambda^{'} X_c{}^{1860} + \boldsymbol{MA}_c - MA_{c,1860} + \epsilon_c$. Each estimate and the associated 95% confidence interval is from a separate regression of the outcome measured in the year specified in the x-axis on the treatment indicator. Outcomes are county-level tabulations from the Decennial Censuses or the Census of Manufactures.

Figure A.23: Excluding Frontier States

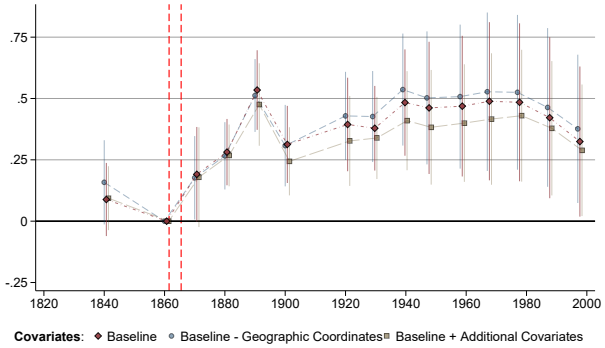
(a) Log Mnf Production Employment



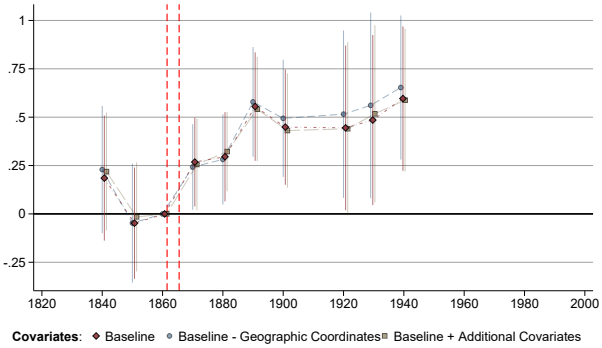
(b) Log Population



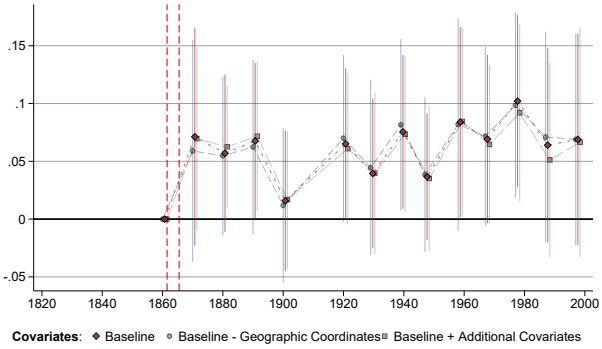
(c) Log Mnf Establishments



(d) Log Manufacturing Production

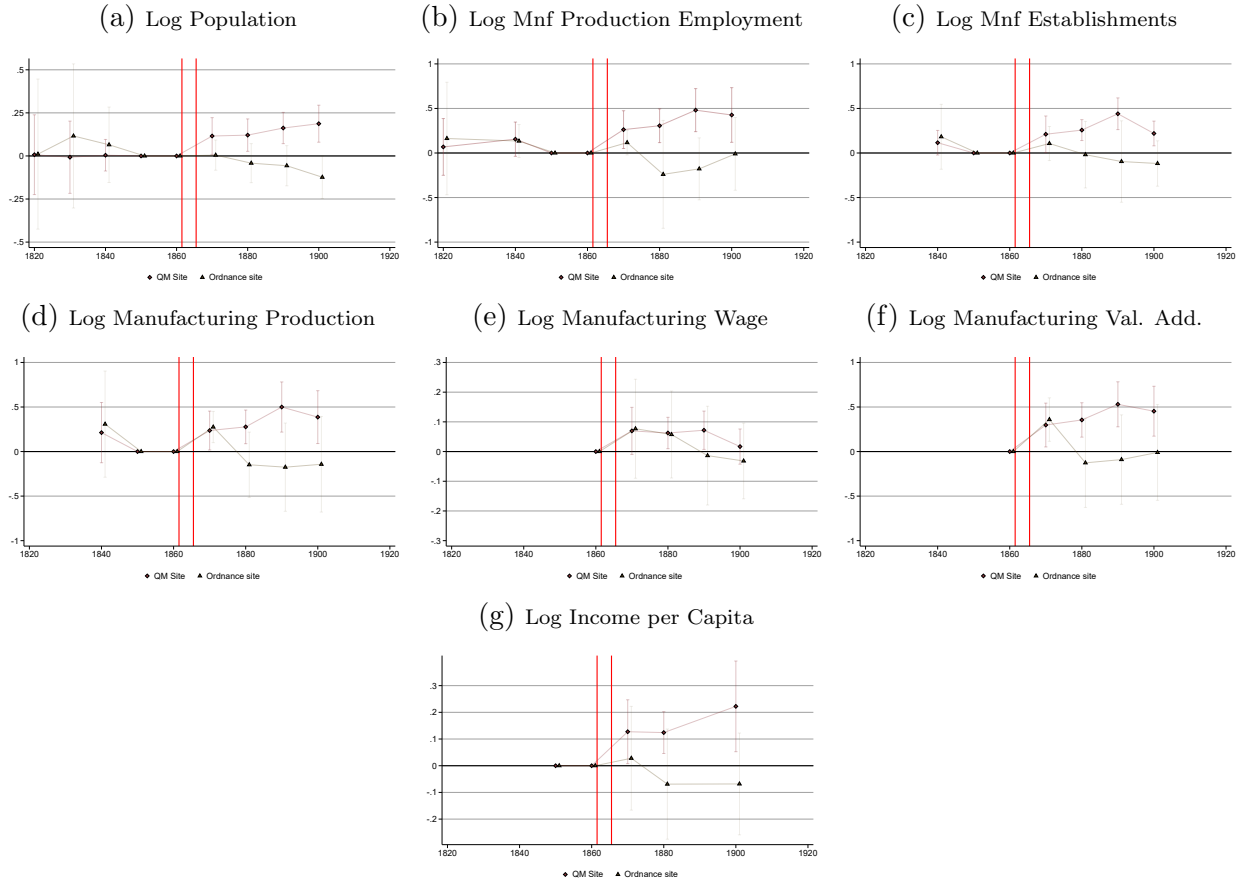


(e) Log Manufacturing Wage



Notes: Figure displays OLS estimates of Equation 1. Each estimate and the associated 95% confidence interval is from a separate regression of the outcome measured in the year specified in the x-axis on the treatment indicator. Outcomes are county-level tabulations from the Decennial Censuses or the Census of Manufactures. Estimation sample excludes Missouri, Kentucky, West Virginia and, Maryland.

Figure A.24: County level Dynamics, By Site Type

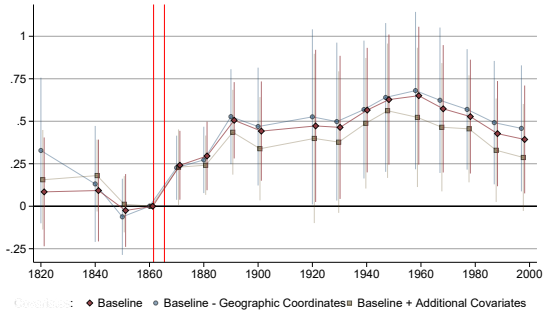


Notes: Figure displays OLS estimates of Equation 1. Each estimate and the associated 95% confidence interval is from a separate regression of the outcome measured in the year specified in the x-axis on the treatment indicator. Outcomes are county-level tabulations from the Decennial Censuses or the Census of Manufactures. All specifications use baseline covariates.

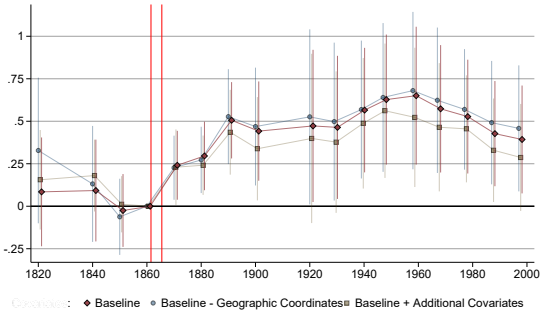
A.1 County-Level Robustness

Figure A.25: County Impact Dynamics, Propensity Score Re-weighting (Trimmed)

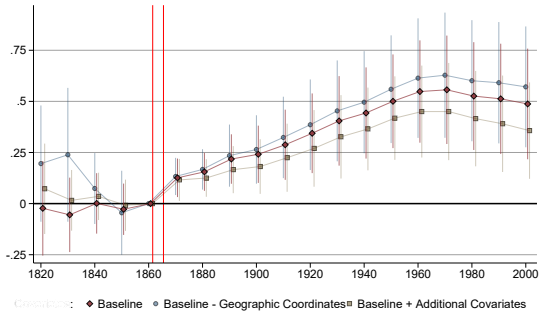
(a) Log Mnf Production Employment (OLS)



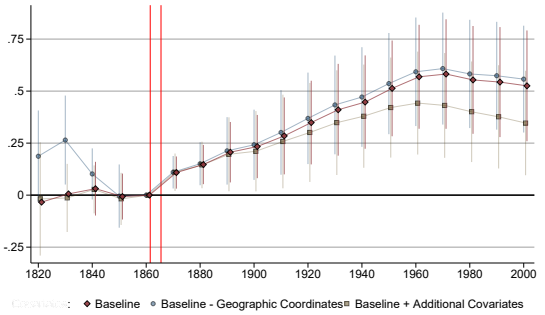
(b) Log Manufacturing Production (IPW)



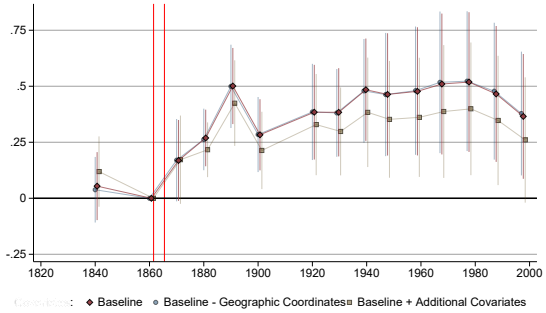
(c) Log Population (OLS)



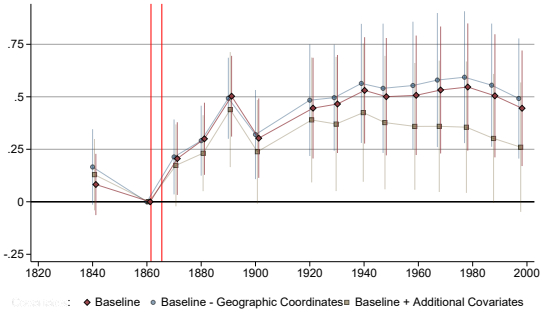
(d) Log Population (IPW)



(e) Log Mnf Establishments(OLS)



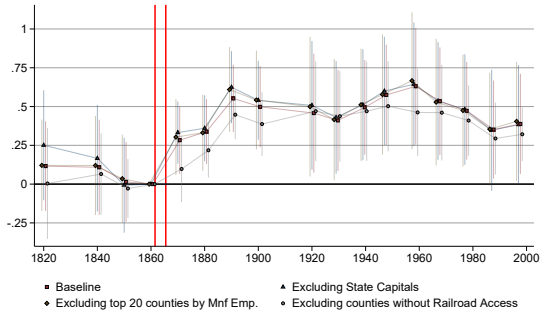
(f) Log Mnf Establishments (IPW)



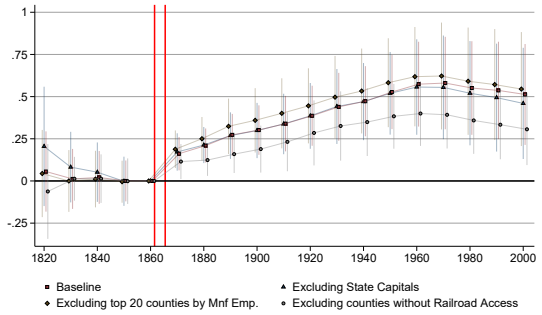
Notes: Figure displays OLS estimates of Equation 1 and IPW estimates of Equation 6 under alternative covariate specifications described in the main text. Each point estimate is obtained separately; propensity score weighted specifications are jointly estimated with the propensity score after initially trimming (**TS**: Trimmed Sample) to the overlap sample. Red lines denote beginning and end of U.S. Civil War.

Figure A.26: County-Level Effects, Sample Restrictions

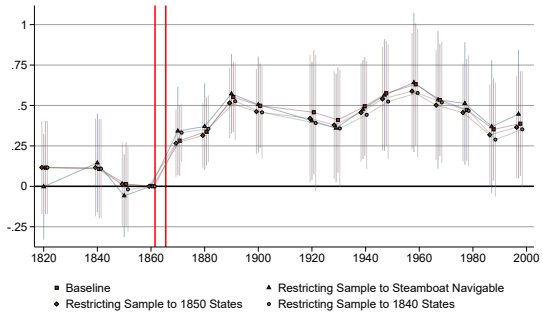
(a) Log Mnf Production Employment



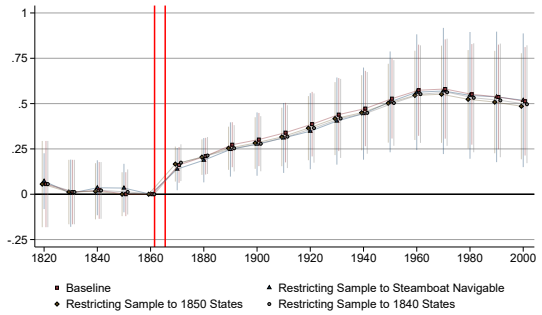
(b) Log Population



(c) Log Mnf Production Employment



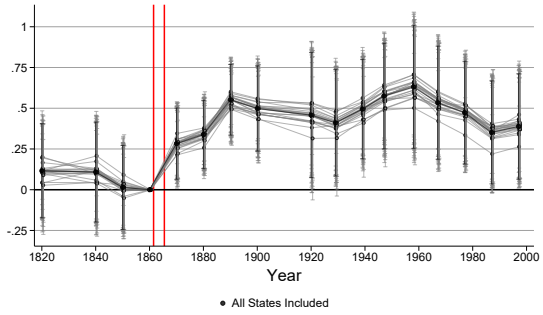
(d) Log Population



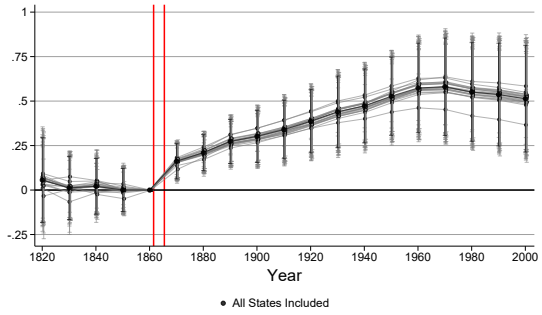
Notes: Figure displays OLS estimates of Equation 1 under alternative covariate specifications described in the main text. Each point estimate is obtained separately. Red lines denote beginning and end of U.S. Civil War.

Figure A.27: County-Level Effects, Dropping One State at a Time

(a) Log Mnf Production Employment



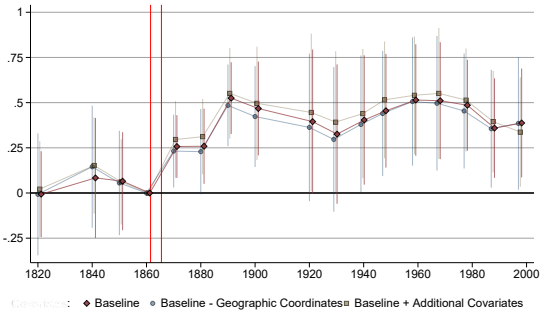
(b) Log Population



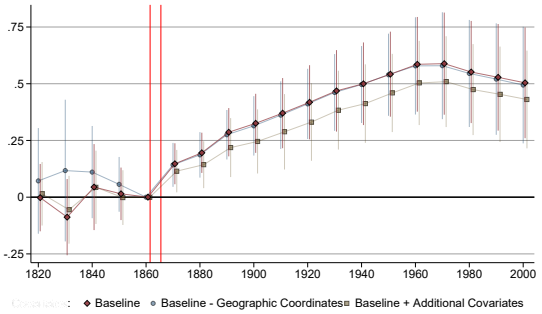
Notes: Figure displays OLS estimates of Equation 1 under alternative covariate specifications described in the main text. Each point estimate is obtained separately. Red lines denote beginning and end of U.S. Civil War.

Figure A.28: County-Level Effects, Including State FEs

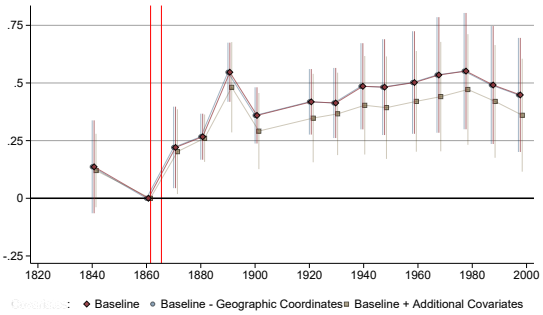
(a) Log Mnf Production Employment



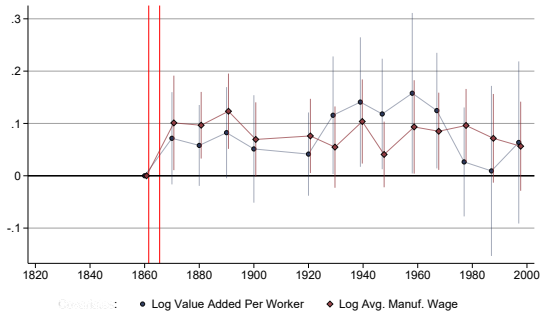
(b) Log Population



(c) Log Mnf. Establishment



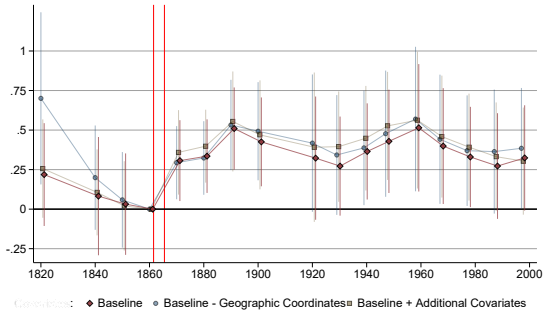
(d) Wage vs Productivity



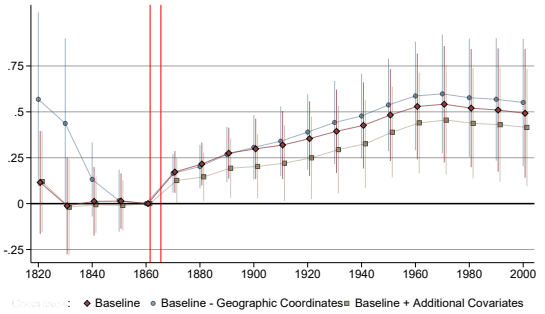
Notes: Figure displays OLS estimates of Equation 1 under alternative covariate specifications described in the main text. Each point estimate is obtained separately. Red lines denote beginning and end of U.S. Civil War.

Figure A.29: County-Level Effects, Excluding Adjoint Counties

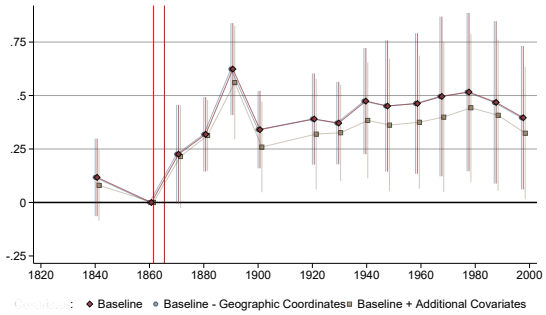
(a) Log Mnf Production Employment



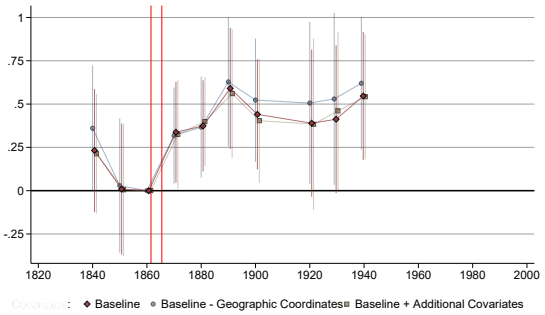
(b) Log Population



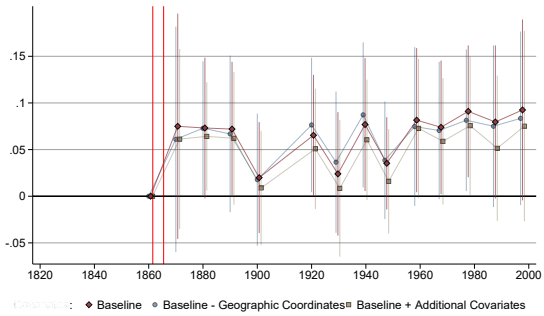
(c) Log Mnf Establishments



(d) Log Mnf Production



(e) Log Mnf Avg. Wage

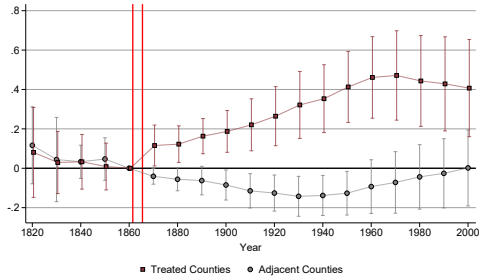


Notes: Figure displays OLS estimates of Equation 1 under alternative covariate specifications described in the main text. Each point estimate is obtained separately. Red lines denote beginning and end of U.S. Civil War.

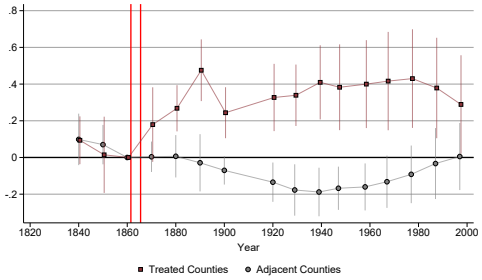
B Miscellaneous

Figure B.1: Dynamics for adjacent counties

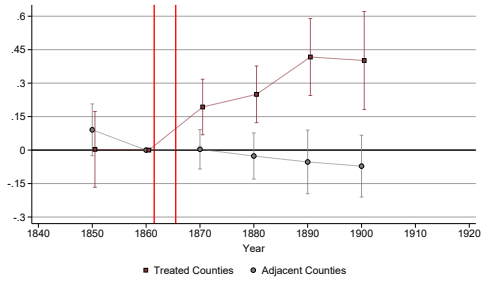
(a) Log Population



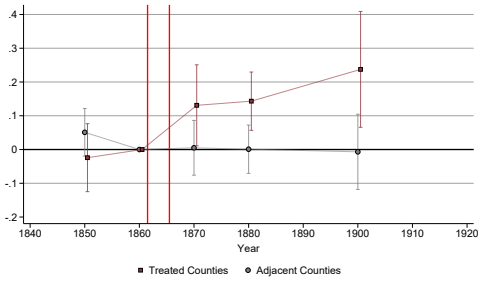
(b) Log Mnf Establishments



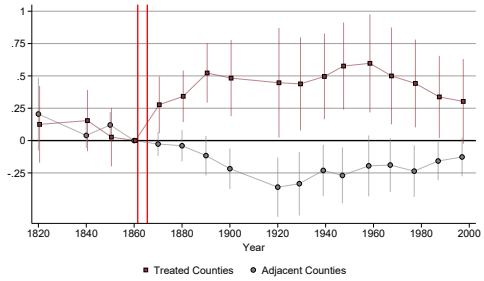
(c)



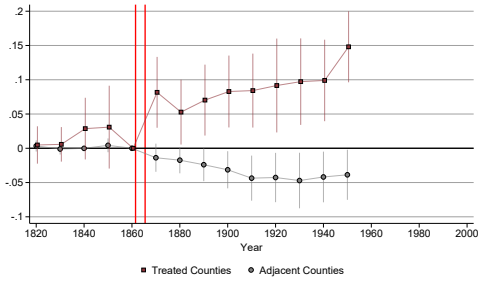
(d) Log Income per Capita



(e) Log Mnf Employment



(f) Share of Urban Population



Notes: Figure displays OLS estimates of Equation 1. Each estimate and the associated 95% confidence interval is from a separate regression of the outcome measured in the year specified in the x-axis on the treatment indicator. Outcomes are county-level tabulations from the Decennial Censuses or the Census of Manufactures. All specifications use baseline covariates.

C Estimated Impacts on County Productivity

C.1 Defining and Decomposing County Productivity

I define county aggregate productivity in manufacturing as total output value minus total input costs which is a is a first-order approximation to welfare under distortions (Basu and Fernald, 2002). We estimate how market access affects county revenues, input expenditures, and productivity. County productivity (Pr_c) takes the following form

$$Pr_c = R_c - \sum_k W_{ck}.X_{ck} \tag{44}$$

where $R_c = P_c.Q_c$ is the county level manufacturing revenue, W_{ck} is cost of a unit of input k and X_{ck} is amount of input k used in manufacturing production.

Impact on log productivity can be written as

$$\begin{aligned}
\frac{\partial \ln Pr_c}{\partial \delta_c} &= \frac{1}{Pr_c}\left[\frac{\partial R_c}{\partial \delta_c} - \sum_k \frac{\partial W_{ck}X_{ck}}{\partial \delta_c}\right] \\
&= \frac{1}{Pr_c}\left[R_c\frac{\partial \ln R_c}{\partial \delta_c} - \sum_k W_{ck}X_{ck}\frac{\partial \ln W_{ck}X_{ck}}{\partial \delta_c}\right] \qquad (45) \\
&= \frac{R_c}{Pr_c}\left[\frac{\partial \ln R_c}{\partial \delta_c} - \sum_k s_{ck}\frac{\partial \ln W_{ck}X_{ck}}{\partial \delta_c}\right], \qquad (46)
\end{aligned}$$

where s_{ck} is revenue share of input k.

To understand the sources of growth in county productivity, I follow Petrin and Levinsohn, 2012 and use production function elasticities (α_{ck}) to further decompose county productivity growth into two components: growth in county revenue total factor productivity (TFPR), or technical efficiency (TE), and growth in county allocative efficiency (AE). The decomposition is as follows:

$$\underbrace{\frac{\partial \ln Pr_c}{\partial \delta_c}}_{\textit{Total Effect}} = \underbrace{\frac{R_c}{Pr_c}\left[\frac{\partial \ln R_c}{\partial \delta_c} - \sum_k \alpha_{ck}\frac{\partial \ln W_{ck}X_{ck}}{\partial \delta_c}\right]}_{\textit{Technical Efficiency (TE)}} + \underbrace{\frac{R_c}{Pr_c}\left[\sum_k (\alpha_{ck} - s_{ck})\frac{\partial \ln W_{ck}X_{ck}}{\partial \delta_c}\right]}_{\textit{Relocative Efficiency (RE)}}. \tag{47}$$

Technical efficiency term is the impact of treatment on county TFPR. Increases in TFPR represent increases in revenue beyond in excess of what could be explained by increases in inputs. If markets are efficient ($\alpha_{ck} = s_{ck}$) growth in TE is the only source of productivity growth.

$$s_{ct}^k = \frac{E_{ct}^k}{R_{ct}}$$

$$\alpha_{ct}^{k} = \sum_{i} \frac{R_{cit}}{\sum_{j} R_{cjt}} \cdot \frac{\sum_{c} E_{cit}^{k}}{\sum_{c} \sum_{\ell} E_{cit}^{\ell}}$$

In case when markets are inefficient, that is due to existence of input frictions or market power, the marginal product of inputs and marginal cost are not equal. Such frictions lead to a *wedge* between marginal product of inputs and marginal costs ($\frac{\alpha_{ck}}{s_{ck}} > 1$) causing inefficiencies. In presence the *gap* between production elasticity and revenue shares ($\alpha_{ck} - s_{ck} > 0$) the increased input use will increase revenue more than input expenditures. The allocative efficiency (AE) term in above equation represents such gains from reallocation, an additional potential source of growth in county productivity even when county TFPR is fixed.

I use industry-county-year level data from census of manufacturers to estimate total county productivity and its two components to estimate the effect of treatment on their growth. The log productivity, in county c and year t is estimated as

$$\frac{R_c}{Pr_c}\left[\ln R_c - \sum_{k} s_{ck} \ln(W_{ck} X_{ck})\right]. \tag{48}$$

The effect on technical efficiency is measured through TFPR growth

$$\frac{R_c}{Pr_c}\left[\ln R_c - \sum_{k} \alpha_{ck} \ln(W_{ck} X_{ck})\right] \tag{49}$$

and the impact on allocative efficincy is measures through AE growth

$$\frac{R_c}{Pr_c}\left[\sum_{k} (\alpha_{ck} - s_{ck}) \ln(W_{ck} X_{ck})\right]. \tag{50}$$

C.2 Estimated Impacts on County Productivity

Table C.1 reports the results from estimating Equation 1. I estimate that the establishment of a QM site has a large and statistically significant effect on manufacturing revenues and input expenditures at the county level. Panel A, based on county–industry data, shows that between 1860 and 1880 the treatment leads to a 32.8% increase in manufacturing revenue, a 40.9% increase in capital expenditure, a 39.8% increase in labor expenditure, and a 34.4% increase in materials expenditure. I also estimate an substantial increase in county productivity of around 32.8%. Treated counties experience an increase in total county revenue that substantially outpaces the increase in total county input expenditures. Panel B reports results using county-level aggregate data for changes between 1860 and 1880. The results are broadly similar to those in Panel A. Panel C presents results for changes between 1860 and 1900. Overall, the estimates are close to those for 1880, with moderate increases in input expenditures and productivity.

Table C.1: Input Use and County Productivity

	Log revenue ($\ln R_c$)	Log capital expenditure ($\ln(W_{cK}X_{cK})$)	Log labor expenditure ($\ln(W_{cL}X_{cL})$)	Log materials expenditure ($\ln(W_{cI}X_{cI})$)	Log productivity $\left(\frac{R_c}{Pr_c}[\ln R_c - \sum_k \alpha_{ck} \ln(W_{ck}X_{ck})]\right)$
Panel A: Using county-industry level data ($y_{1880} - y_{1860}$)					
QM	0.328***	0.409***	0.357***	0.344***	0.315**
	(0.109)	(0.097)	(0.115)	(0.112)	(0.126)
Panel B: Using agg. county level data ($y_{1880} - y_{1860}$)					
QM	0.353***	0.409***	0.425***	0.344***	0.343**
	(0.106)	(0.097)	(0.112)	(0.110)	(0.146)
Panel C: Using agg. county level data ($y_{1900} - y_{1860}$)					
QM	0.473***	0.466***	0.505***	0.467***	0.486***
	(0.145)	(0.130)	(0.153)	(0.144)	(0.159)
Panel C: Using agg. county level data ($y_{1900} - y_{1860}$)					
QM	0.473***	0.466***	0.505***	0.467***	0.486***
	(0.145)	(0.130)	(0.153)	(0.144)	(0.159)
N	961	961	961	961	961

Standard errors clustered by state in parentheses

Table C.2 presents the decomposition of productivity into technical efficiency and allocative efficiency. Most of the estimated impact on log productivity is driven by growth in county-level allocative efficiency (AE), with no statistically significant contribution from county-level TFPR growth. When using county-level aggregate data and assuming a single production function for all manufacturing industries, I obtain similar estimates for 1880. The effects on productivity and its components remain largely unchanged going from 1880 to 1900.

Table C.2: Impacts on County Productivity, Decomposed into TFPR and AE

	Log county productivity $\left(\frac{R_c}{Pr_c}[\ln R_c - \sum_k s_{ck} \ln(W_{ck}X_{ck})]\right)$	TFPR $\left(\frac{R_c}{Pr_c}[\ln R_c - \sum_k \alpha_{ck} \ln(W_{ck}X_{ck})]\right)$	Allocative Efficiency $\left(\frac{R_c}{Pr_c}[\sum_k (\alpha_{ck} - s_{ck}) \ln(W_{ck}X_{ck})]\right)$
	(1)	(2)	(3)
Panel A: Using county-industry (32-industries) level data ($y_{1880} - y_{1860}$)			
QM	0.315**	-0.098	0.413***
	(0.126)	(0.080)	(0.107)
Panel C: Using county level data ($y_{1900} - y_{1860}$)			
QM	0.486***	0.051	0.436***
	(0.159)	(0.087)	(0.139)
Panel C: Using county level data ($y_{1900} - y_{1860}$)			
QM	0.486***	0.051	0.436***
	(0.159)	(0.087)	(0.139)
N	961	961	961

Standard errors clustered by state in parentheses

C.2.1 Sources of Growth in County Allocative Efficiency (AE)

Table C.3, panel A, reports that the estimated increase in county AE is largely driven by increases in materials, followed by labor.

Table C.3: Sources of Growth in County AE

	Capital	Material	Labor
Panel A: AE by input ($y_{1880} - y_{1860}$)			
QM	-0.011 (0.016)	0.343*** (0.106)	0.081** (0.034)
Panel B: County input wedge ($y_{1880} - y_{1860}$)			
QM	-0.109 (0.078)	-0.088 (0.089)	-0.112 (0.068)
Panel C: County input gap ($y_{1880} - y_{1860}$)			
QM	-0.003 (0.004)	0.008 (0.009)	-0.008 (0.006)

Standard errors clustered by state in parentheses

C.3 Historical Documents







2000 ARMY HORSES WANTED!

I want to purchase immediately at the Government Stables at this station,

TWO THOUSAND ARMY HORSES!

For which I will pay the prices named below, IN CASH. Horses must pass inspection under the following regulations, to wit:

FOR HORSES

Sound in all particulars, well broken, in full flesh and good condition, from fifteen (15) to sixteen (16) hands high, from five (5) to nine [9] years old, and well adapted in every way to Cavalry purposes—price

160 DOLLARS!

FOR HORSES

Of DARK Color, sound in all particulars, strong, quick and active, well broken, square trotters in harness, in good flesh and condition, from six [6] to ten [10] years old, not less than fifteen and one half [15 1-2] hands high, weighing not less than ten hundred and fifty [1050] pounds each, and adapted to Artillery service,

170 DOLLARS!

N. B. VAN SLYKE,
CAPT. & A. Q. M.

Assistant Quartermaster's Office, Madison, Wis., March 22, 1865.