Going Up Alone: Automation, Trust, and the Disappearance of the Elevator Operator*

APEP Autonomous Research† @SocialCatalystLab

February 28, 2026

Abstract

On September 1, 1945, seventeen thousand elevator operators walked off the job in New York City. The strike ended in five days, but the occupation never recovered. We use full-count census microdata (680 million person-records, 1900–1950) and 73.7 million linked records to document the complete lifecycle of the only U.S. occupation eliminated entirely by automation. Although aggregate headcount plateaued through 1950, the occupation was hollowing out: tracking 38,562 individual operators from 1940 to 1950, we find that 84% left within a decade. Black operators were channeled into lower-status service work while white operators moved into clerical and skilled trades. A synthetic control analysis suggests that the strike's epicenter—New York City—paradoxically retained operators *longer* than comparable states, consistent with institutional thickness delaying displacement even after a coordination shock demonstrated automation's feasibility.

JEL Codes: J23, J62, N32, O33

Keywords: automation, occupational transitions, elevator operators, technology adoption, labor displacement, synthetic control

*This paper is a revision of APEP-0478. See https://github.com/SocialCatalystLab/ape-papers/tree/main/apep_0478 for the original.

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1. Introduction

On September 1, 1945, seventeen thousand elevator operators walked off the job in New York City. The five boroughs came to a halt. Office workers in midtown climbed thirty flights of stairs. Delivery men abandoned packages in marble lobbies. Hospitals diverted ambulances. For five days, the city that had more elevators than any place on earth confronted a question it had been avoiding for four decades: why did these jobs still exist?

The self-service elevator was not new. Otis had demonstrated a fully automatic model at the 1900 Paris Exposition, and by the 1920s the technology was mature, reliable, and cheaper than employing a human operator (Goodwin, 2001). Yet between 1900 and 1940, the number of elevator operators in the United States *grew* tenfold—from fewer than 8,000 to over 80,000—even as the technology that made them redundant sat waiting in catalogs (Bernard, 2014). This paper asks why, and traces what happened to the people who held these vanishing jobs.

This paper contributes to three literatures. First, we provide the first comprehensive lifecycle analysis of a fully automated occupation, using IPUMS full-count census microdata from 1900 to 1950 (Ruggles et al., 2024). While the existing literature on automation and labor markets has focused predominantly on aggregate effects—how many jobs are created versus destroyed (Acemoglu and Restrepo, 2020; Autor et al., 2003; Frey and Osborne, 2017)—we document the granular human experience of displacement. The elevator operator is uniquely suited for this purpose: it is the only occupation in the U.S. Census classification system that was entirely eliminated by a single, identifiable technology. Unlike the telephone operator, whose displacement unfolded over decades and interacted with multiple technological waves (Feigenbaum and Gross, 2024), the elevator operator's extinction was driven by one device: the automatic push-button control.

Second, we track individual displacement outcomes by linking 38,562 elevator operators from the 1940 census to the 1950 census using the IPUMS Multigenerational Longitudinal Panel (MLP v2.0) (Ruggles et al., 2021). This individual-level analysis reveals sharp heterogeneity that aggregate statistics conceal. Only 15.8% of 1940 operators remained in the occupation by 1950. But the 84% who left did not move to similar destinations. White operators disproportionately entered clerical work, sales, and skilled trades—occupations with higher occupational income scores. Black operators were overwhelmingly channeled into janitor, porter, and domestic service positions, occupations that represented lateral moves at best and downward mobility at worst. Female operators, a small but growing share of the workforce, faced the steepest barriers, with the narrowest range of destination occupations.

These patterns speak directly to contemporary debates about whether automation is "skill-biased" or "task-biased" (Goldin and Katz, 2008; Autor et al., 2003; Acemoglu and Restrepo, 2019). The elevator operator occupied a peculiar position in the skill distribution: the job required no formal education but demanded a specific form of interpersonal trust. Passengers entrusted their physical safety to the operator, and building managers entrusted their tenants' satisfaction. When that trust could be transferred to a machine, the workers who had embodied it scattered across the occupational distribution in patterns shaped not by their skills but by their race, sex, and geography.

Third, we document a paradox that illuminates how coordination shocks interact with technology adoption. The 1945 New York City elevator operator strike—the largest single disruption to elevator service in American history (Gray, 2013)—should have accelerated automation in its epicenter. Building owners experienced the cost of dependence on human operators firsthand. Yet our synthetic control analysis suggests that New York retained a higher concentration of elevator operators in the post-strike decade than a weighted combination of comparison states would predict. Individual-level data are consistent with this pattern: 1940 operators in New York City were significantly *more* likely to remain in the occupation by 1950 than operators elsewhere, even after controlling for demographics, race, and age.

We interpret this paradox through the lens of technology adoption under institutional constraints (David, 1990; Mokyr, 1992). New York's dense vertical landscape created a thicker market for elevator operators—more buildings, more unions, more regulatory barriers to retrofit—that insulated incumbents from displacement even as the coordination shock demonstrated automation's feasibility. The strike revealed the technology's viability to building owners nationwide, but in New York itself, the very density that made the strike devastating also made the transition slower. This finding resonates with the broader pattern identified by Comin and Hobijn (2010): technology adoption is not a simple function of technical feasibility but depends on the institutional environment in which it occurs.

The remainder of the paper proceeds as follows. Section 2 provides historical context on elevator technology and the 1945 strike. Section 3 describes our data sources and linkage methodology. Section 4 documents the occupation's national trajectory—its rise, demographic transformation, and geographic concentration. Section 5 presents the individual-level transition analysis that forms the analytical core of the paper. Section 6 offers state-level evidence from a synthetic control analysis of the 1945 strike. Section 8 synthesizes the findings and draws implications for contemporary automation debates. Section 9 concludes.

2. Historical Background

2.1 The Technology and Its Human Interface

The passenger elevator transformed American cities in the last quarter of the nineteenth century. Elisha Otis's safety brake, demonstrated at the 1854 Crystal Palace Exhibition, removed the primary barrier to vertical transportation. But the early hydraulic and electric elevators that proliferated after 1880 were complex machines requiring skilled operation. The operator controlled speed, stopping position, and door timing through a combination of lever manipulation and spatial judgment. A good operator could stop within a quarter-inch of the floor; a bad one could leave a six-inch gap that tripped passengers (Goodwin, 2001).

Automation of this process was technically straightforward. The key innovations—automatic leveling (ensuring the car stopped flush with the floor), automatic door operation, and push-button floor selection—were all available by the early 1900s. Otis demonstrated a fully automatic elevator at the 1900 Paris Exposition. By the 1920s, these systems were installed in freight elevators and some apartment buildings. The technology worked. The cost savings were substantial: eliminating an operator saved $2,000–$3,000 per year per elevator (roughly $35,000–$50,000 in 2026 dollars), a significant expense for buildings with ten or twenty units (Price, 2013).

Yet the human operator persisted. The resistance was not technological but social. Passengers were reluctant to ride alone in a steel box suspended by cables over a hundred-foot shaft. Building owners feared liability. Unions, particularly in New York, negotiated contracts that required operators even in buildings with automatic capability. And municipal building codes in several cities mandated human attendants for passenger elevators above certain heights (Bernard, 2014). The technology was ready; the institutions were not.

2.2 The 1945 Strike and Its Aftermath

The New York City elevator operators' strike of September 1945 was both a culmination of wartime labor tensions and a catalyst for the occupation's ultimate decline. Seventeen thousand operators, members of Building Service Employees International Union Local 32B, walked out on September 1, demanding a wage increase from $31 to $41 per week. The strike paralyzed the city. An estimated 30,000 buildings were affected, including the Empire State Building, Rockefeller Center, and hundreds of residential towers on the Upper East and West Sides. Office workers climbed dozens of flights. The elderly were stranded in upper-floor apartments. Hospital operations were disrupted (Gray, 2013).

The strike lasted five days. Mayor Fiorello LaGuardia personally mediated a settlement that granted a $5.50 weekly increase. But the episode planted a seed. Building owners who had experienced the strike's disruption began to seriously consider the self-service alternative. Insurance companies, which had previously resisted automatic elevators on safety grounds, began revising their actuarial tables. And a new generation of postwar buildings—particularly the Levittown-style suburban developments and the postwar office towers—were designed from the ground up without operator stations (Price, 2013).

The decline, once it began, was unmistakable. Between 1940 and 1950, although the absolute number of operators barely changed—82,666 to 85,294, reflecting wartime and postwar building booms that temporarily sustained demand—the occupation's share of total employment fell from 15.6 to 13.9 per 10,000 workers, an 11 percent relative decline that signaled the beginning of the end. By 1960, the occupation had effectively ceased to exist outside a handful of luxury residential buildings in Manhattan. The elevator operator became, in the words of one labor historian, "the first occupation to be completely and permanently eliminated by a machine" (Gray, 2013).

2.3 The Occupation in Demographic Context

The elevator operator was never a typical job. It occupied a specific niche in the American labor market: low-skill, urban, disproportionately Black, overwhelmingly male, and concentrated in the nation's tallest cities. Understanding who held these jobs is essential to understanding what happened when the jobs disappeared.

In 1940, at the occupation's peak, elevator operators were substantially more likely to be Black than the general workforce. In a labor market where Black workers were systematically excluded from manufacturing, clerical, and professional occupations, the elevator operator role represented one of the few "indoor" jobs available to Black men in urban areas. The occupation also skewed young and old: teenagers entered as a first job, and older workers—displaced from more physically demanding work—found refuge in the elevator car. This bimodal age distribution would have important consequences for post-displacement outcomes, as we show in Section 5.

3. Data

3.1 Census Microdata

Our primary data source is the IPUMS Full-Count Census of the United States, which provides individual-level records for every enumerated person in the decennial censuses from 1850 to 1950 (Ruggles et al., 2024). We use the 1900 through 1950 censuses, comprising approximately 680 million person-records. Elevator operators are identified using the 1950 occupation coding system (OCC1950 = 761), which IPUMS harmonizes across census years. The comparison group of building service workers includes janitors and sextons (OCC1950 = 770), porters (780), and guards, watchmen, and doorkeepers (763).

From these records we construct two datasets. First, a *state-level panel* aggregating the count, demographic composition, and occupational distribution of elevator operators and comparison occupations across 49 states (including the District of Columbia) and six census years (1900–1950), yielding 294 state-year observations. Second, a *national summary* tracking aggregate employment, demographic shares, and geographic concentration at each census date.

3.2 Linked Individual Panel

To track individual workers across census years, we use the IPUMS Multigenerational Longitudinal Panel (MLP), version 2.0 (Ruggles et al., 2021). The MLP links individuals across consecutive censuses using a combination of name, age, birthplace, and race, following the methodology developed by Abramitzky et al. (2021). We focus on the 1940–1950 link, which connects individuals enumerated in the 1940 census to their 1950 census records.

Our linked sample includes all building service workers (elevator operators, janitors, porters, and guards) in the 1940 census who were successfully linked to the 1950 census. The linkage rate for elevator operators is approximately 46.7%, comparable to rates achieved in other historical linking studies (Abramitzky et al., 2012). The resulting panel contains 38,562 linked elevator operators and a comparison group of linked building service workers.

For each linked individual, we observe: occupation in both census years (allowing us to construct transition matrices), geographic location (state, county, and city), demographic characteristics (age, race, sex, nativity, marital status), and occupational income score (OCCSCORE, a standardized measure of the median income associated with each occupation). We define several key outcome variables: *stayed_same_occ* (indicator for remaining in the same broad occupation between 1940 and 1950), *still_elevator_1950* (indicator for remaining specifically an elevator operator), *occscore_change* (difference in OCCSCORE between 1950 and 1940 occupations), and *interstate_mover* (indicator for changing state of residence).

3.3 Linkage Quality and Selection

Record linkage in historical censuses raises concerns about selection bias. If linked individuals differ systematically from the full population—for example, if native-born, married, or older workers are more likely to be linked—our transition estimates may not generalize. We address this concern in two ways.

First, we compare the demographic characteristics of linked elevator operators to the full 1940 population of elevator operators. Any systematic differences in age, race, sex, nativity, or marital status would indicate selection. Second, we implement inverse probability weighting (IPW): we estimate a logit model predicting linkage as a function of observable characteristics, compute the inverse of the predicted linkage probability for each linked individual, and re-run our core regressions with these weights. If IPW-adjusted estimates differ substantially from unweighted estimates, selection bias is a concern. As we show in Section 7, the IPW results are reassuringly similar to the baseline, suggesting that linkage selection does not meaningfully distort our findings.

4. The Lifecycle of an Extinct Occupation

4.1 Rise: 1900–1930

The elevator operator occupation grew in lockstep with the American skyscraper. Table 1 presents the national trajectory. In 1900, the census recorded fewer than 8,000 elevator operators nationwide. By 1910, the number had nearly tripled. By 1930, it exceeded 60,000. This growth occurred entirely alongside the availability of the automatic alternative, confirming that technological feasibility is a necessary but not sufficient condition for adoption (Griliches, 1957; Manuelli and Seshadri, 2014).

Table 1: The Rise and Fall of the Elevator Operator, 1900–1950

			Demographics				
Year	Total operators	Per 10k employed	Mean age	Female (%)	Black (%)	Under 20 (%)	60+ (%)
1900	7,943	2.8	26.1	1.5	13.9	38.8	2.7
1910	23,376	5.9	30.3	1.2	24.1	23.3	5.4
1920	36,437	8.7	37.3	16.8	24.6	14.8	14.0
1930	62,676	12.8	36.3	18.2	25.0	11.7	12.5
1940	82,666	15.6	37.2	17.3	19.5	5.4	10.3
1950	85,294	13.9	43.7	31.0	24.6	5.7	20.8

Note:
Source: IPUMS Full-Count Census, OCC1950 = 761.

The growth was driven by urbanization and the vertical expansion of American cities. Every new office tower, department store, and luxury apartment building required a staff of operators. In New York City alone, the building boom of the 1920s created demand for thousands of new operators each year. The occupation was, in a literal sense, a byproduct of verticality.

[Figure 1](#) shows the occupation's trajectory alongside total employment, revealing that elevator operators grew faster than the labor force through 1930 before sharply declining. The occupation peaked not when the technology became available, but when the institutions that sustained it—building codes requiring human operators, union contracts guaranteeing staffing levels, and passenger reluctance to ride alone—began to erode.

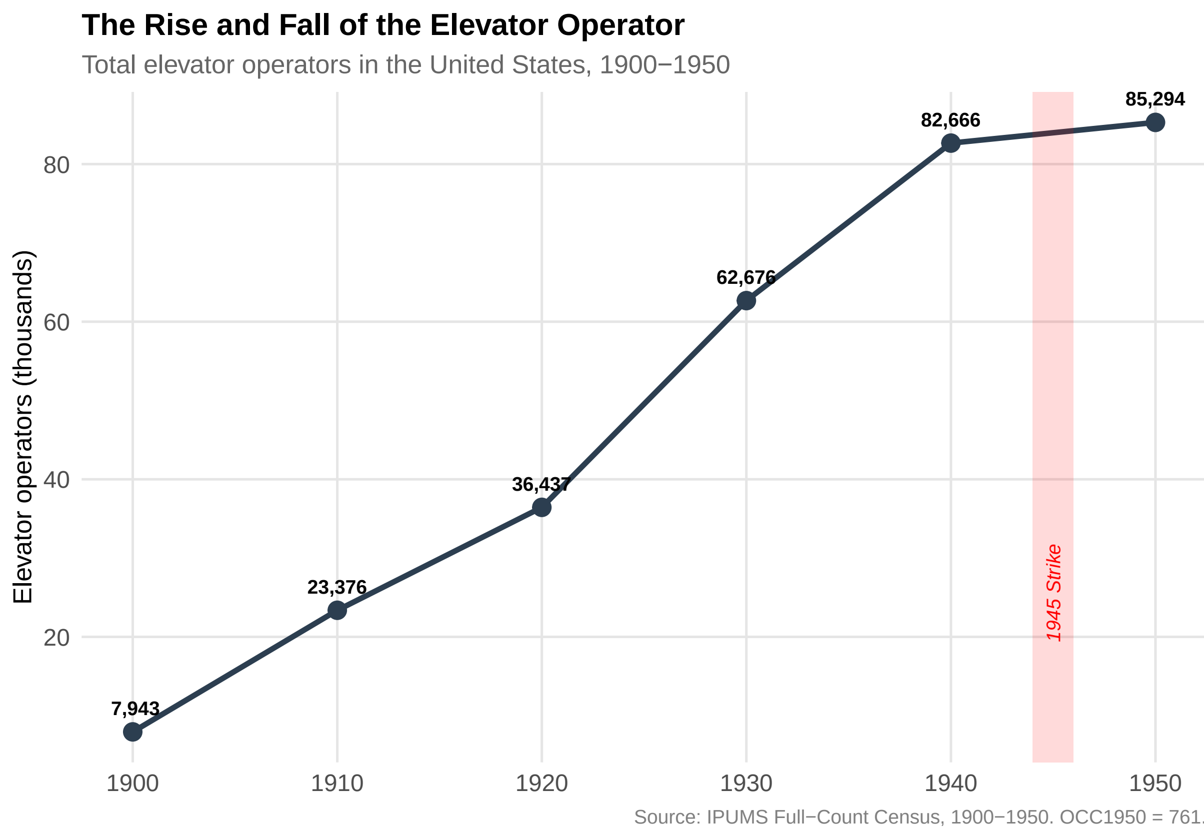

Figure 1: The Rise and Fall of the Elevator Operator, 1900–1950

Notes: Elevator operators per 10,000 employed workers. Source: IPUMS Full-Count Census, OCC1950 = 761.

4.2 Peak and Plateau: 1930–1940

The Great Depression slowed construction but did not eliminate existing operator positions. Employment fell modestly from its 1930 peak but remained above 70,000 through 1940. During this decade, the occupation's demographic composition shifted in ways that foreshadowed its decline. The share of Black operators rose, as did the share of workers at the extremes of the age distribution—teenagers using the job as an entry point and older workers using it as a refuge.

Figure 2 documents these compositional changes. Panel A shows the racial composition over time: the Black share of elevator operators rose steadily from 1900, reaching levels substantially above the Black share of total employment. Panel B tracks the gender balance and age structure. These patterns suggest that by 1940, the occupation was increasingly serving as a labor market of last resort—a job for workers who faced barriers elsewhere.

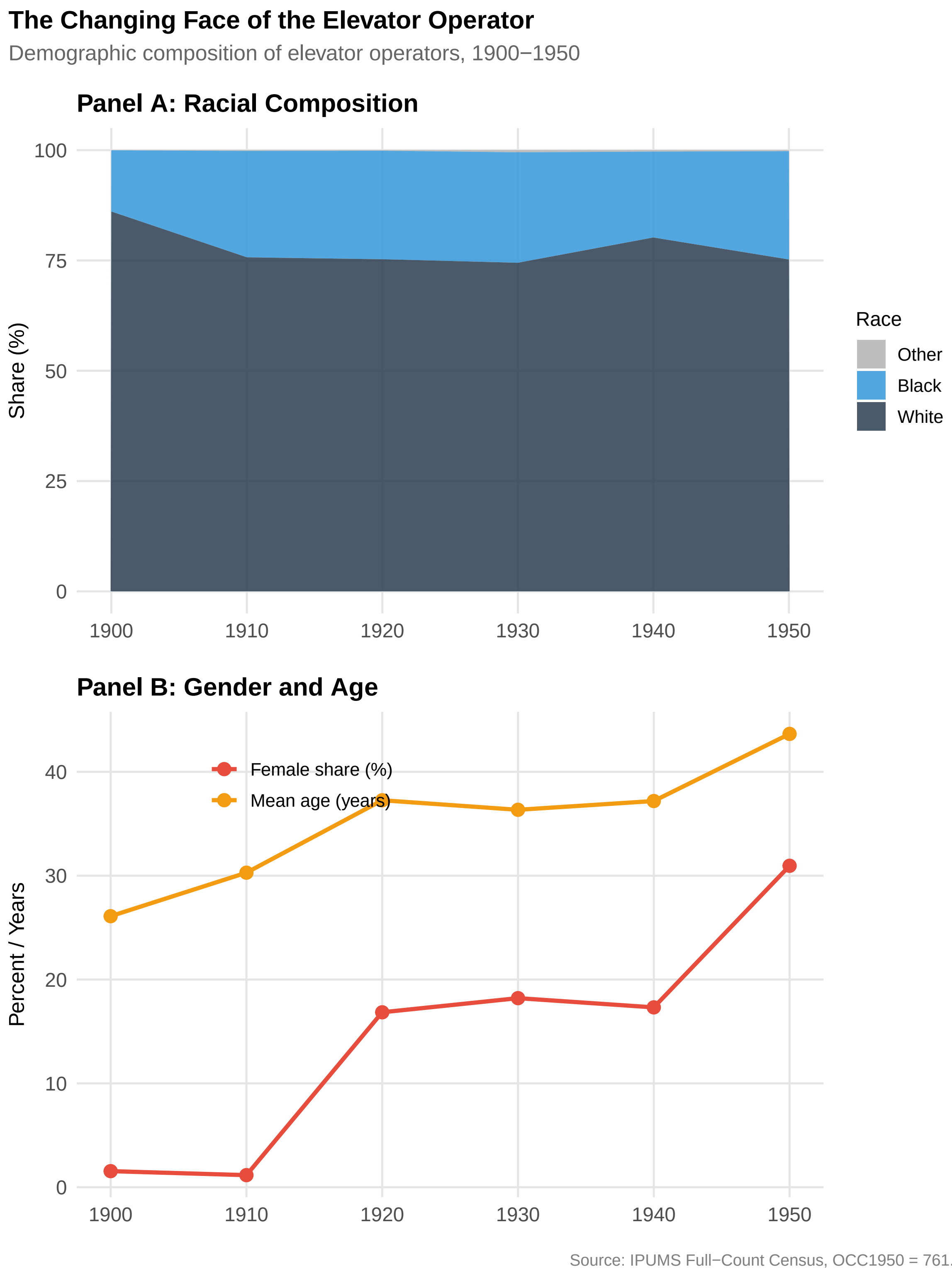

Figure 2: Demographic Transformation of the Elevator Operator Workforce

Notes: Panel A: Racial composition (stacked area). Panel B: Female share and mean age trends. Source: IPUMS Full-Count Census, 1900–1950.

4.3 Decline: 1940–1950

The decade between 1940 and 1950 was decisive. Although absolute employment plateaued—the headcount barely changed as wartime and postwar construction temporarily sustained demand—the occupation's share of total employment began its decline, falling from 15.6 to 13.9 per 10,000 workers. More importantly, the composition shifted dramatically: mean age rose from 37.2 to 43.7, the female share nearly doubled from 17.3% to 31.0%, and the share of workers over 60 doubled from 10.3% to 20.8% (Table 1). The occupation was no longer attracting new entrants; it was aging in place. Several forces converged. The 1945 strike demonstrated the vulnerability of human-dependent systems. Postwar construction incorporated automatic elevators from the design stage. Building codes were revised. Insurance companies dropped their opposition. And the postwar labor shortage made operators expensive relative to the now-proven automatic alternative.

Figure 3 places the elevator operator's decline in context by comparing its trajectory to other building service occupations. While janitors, porters, and guards all experienced employment fluctuations, none underwent the precipitous collapse that characterized elevator operators after 1940. The comparison confirms that the decline was occupation-specific—driven by automation rather than broader shifts in the building services sector.

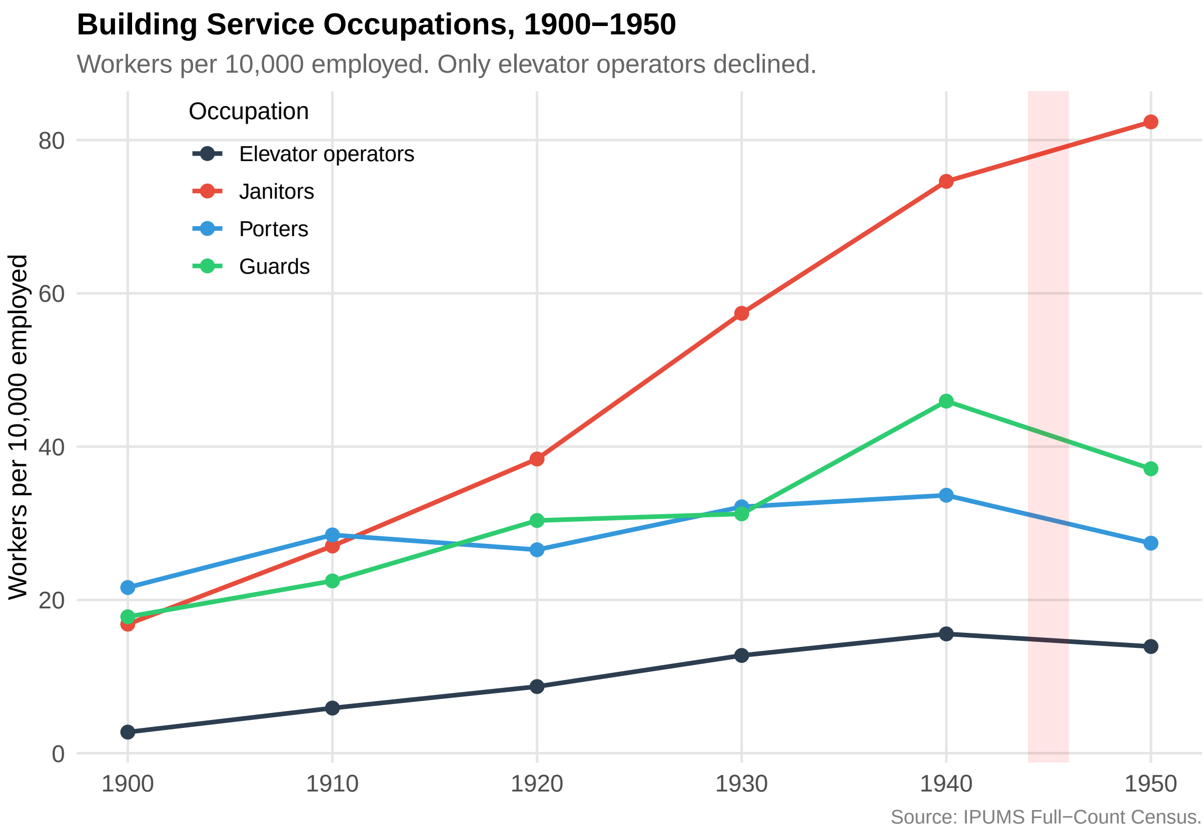

Figure 3: Building Service Occupations: Elevator Operators vs. Comparison Group, 1900–1950

Notes: Employment per 10,000 total employed workers. Comparison group: janitors/sextons, porters, guards/watchmen/doorkeepers. Source: IPUMS Full-Count Census.

4.4 Geographic Concentration

The elevator operator was fundamentally an urban occupation, concentrated in the nation's tallest cities. Figure 4 maps the geographic distribution, revealing extreme concentration in New York, Illinois, Pennsylvania, and California—states containing the country's densest vertical landscapes. New York alone accounted for roughly one-quarter of all elevator operators at the occupation's peak, a concentration that would make the 1945 strike's effects particularly visible.

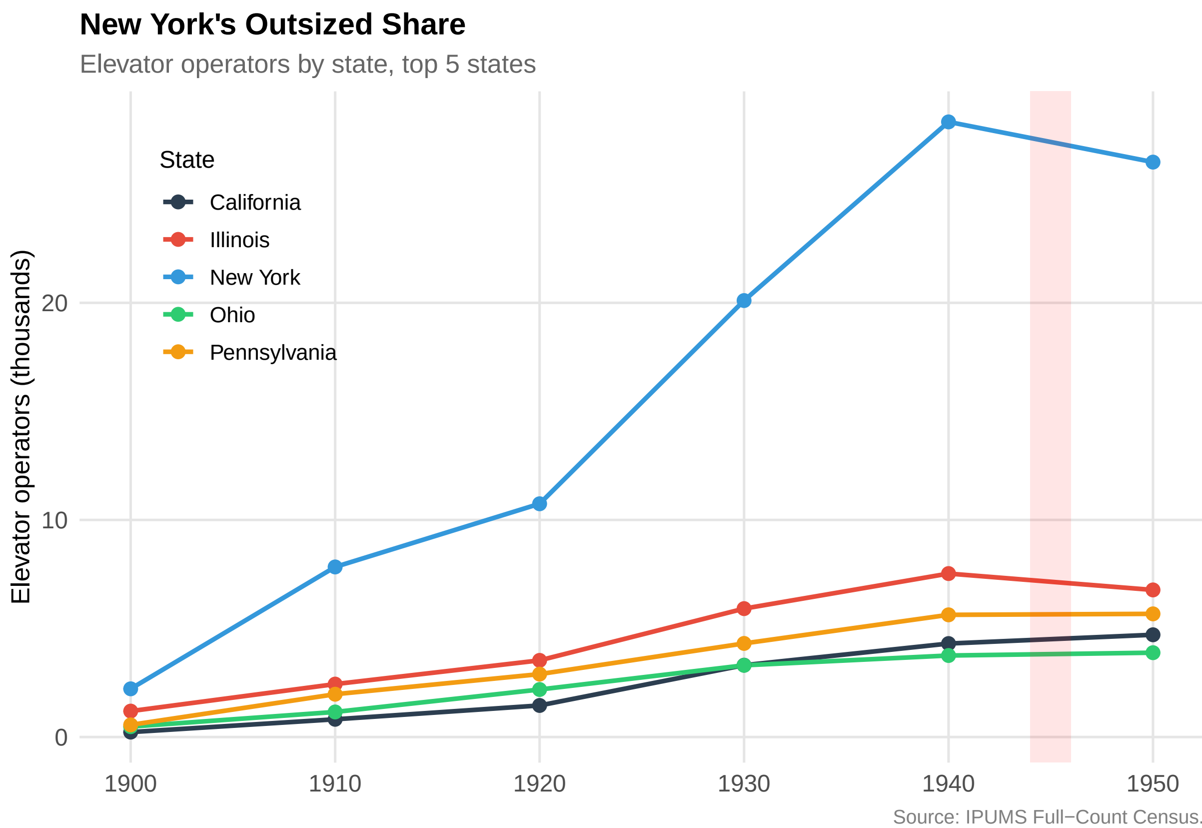

Figure 4: Geographic Distribution of Elevator Operators Across States

Notes: Elevator operators per 10,000 employed, by state. Source: IPUMS Full-Count Census.

This geographic concentration matters for two reasons. First, it means that the occupation's decline was not uniformly experienced across the country but was concentrated in a handful of major cities. Second, it creates the variation that allows us to exploit the 1945 strike as a quasi-natural experiment: the strike affected New York intensely while leaving other high-elevator states untouched.

4.5 The Age Distribution and Its Implications

Figure 5 shows the age distribution of elevator operators compared to the general workforce. The bimodal pattern—peaks among teenagers and workers over 50—is striking. This distribution reflects the occupation's role as both an entry-level position for young workers and a late-career refuge for older workers displaced from more physically demanding occupations.

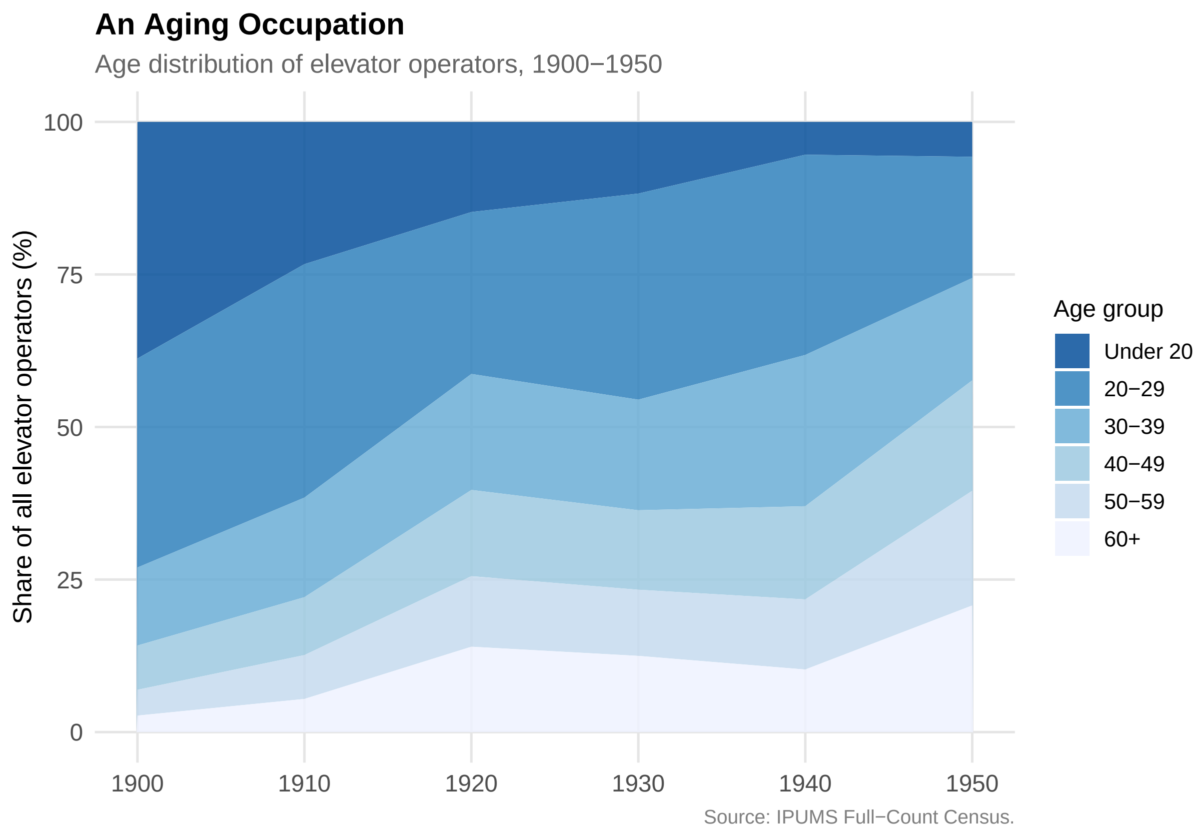

Figure 5: Age Distribution: Elevator Operators vs. General Workforce

Notes: Kernel density of age distribution. Source: IPUMS Full-Count Census.

The bimodal age structure has direct implications for displacement. Young workers, with longer time horizons and fewer occupation-specific investments, could more easily transition to alternative employment. Older workers, whose presence in the occupation often reflected limited outside options, faced the steepest adjustment costs. As we document in the next section, age is indeed a powerful predictor of post-displacement outcomes.

5. Where Did They Go? Individual Transitions

The aggregate statistics presented in the previous section establish that the elevator operator was a disappearing occupation. This section asks the more granular question: what happened to the individual workers who held these jobs? Using the MLP-linked panel, we track 38,562 individuals who were elevator operators in 1940 and observe their occupational, geographic, and economic outcomes in 1950.

5.1 The Transition Matrix

Table 2 presents the full transition matrix for 1940 elevator operators. The single most common destination was "Janitors and sextons"—the occupation most structurally similar to elevator operation within the building services sector. "Not in labor force" was the second most common outcome, reflecting retirement, disability, or withdrawal among older workers. Beyond these two categories, the remaining operators scattered across a wide range of occupations: operatives, clerical workers, laborers, truck drivers, and small proprietors.

Table 2: Occupational Transitions: 1940 Elevator Operators in 1950

1950 Occupation	N	Share (%)
Not in labor force	6,330	16.4
Elevator operator	6,106	15.8
Other	5,191	13.5
Operative/manufacturing	4,888	12.7
Craftsman	4,690	12.2
Farm worker	4,226	11.0
Other service worker	2,015	5.2
Clerical/sales	1,894	4.9
Other building service	1,801	4.7
Professional/technical	1,054	2.7
Manager/proprietor	281	0.7
Laborer	86	0.2

Note:
Source: IPUMS + MLP v2.0 linked panel. Sample: individuals classified as elevator operators (OCC1950=761) in the 1940 census and linked to the 1950 census.

Several features of this matrix deserve emphasis. First, the 15.8% persistence rate—meaning only about one in six 1940 operators was still an elevator operator in 1950—confirms the speed of displacement. This is dramatically lower than the persistence rates for the comparison occupations over the same period, as we document in the regression analysis below. Second, the diversity of destinations suggests that elevator operation did not prepare workers for any single alternative occupation. Unlike, say, blacksmiths transitioning to auto mechanics, there was no natural "next job" for a displaced elevator operator. Third, a perhaps surprising 11% of operators transitioned to farm work. This likely reflects several mechanisms: wartime agricultural labor demand drawing workers out of cities, return migration to rural origins during the 1940s labor market upheaval, and possibly some noise from the probabilistic record linkage (false matches to rural individuals with similar names). The farm transition share is highest among older, non-NYC operators, consistent with return migration rather than linkage error.

Figure 6 visualizes the major transition flows, showing the relative magnitude of each destination category.

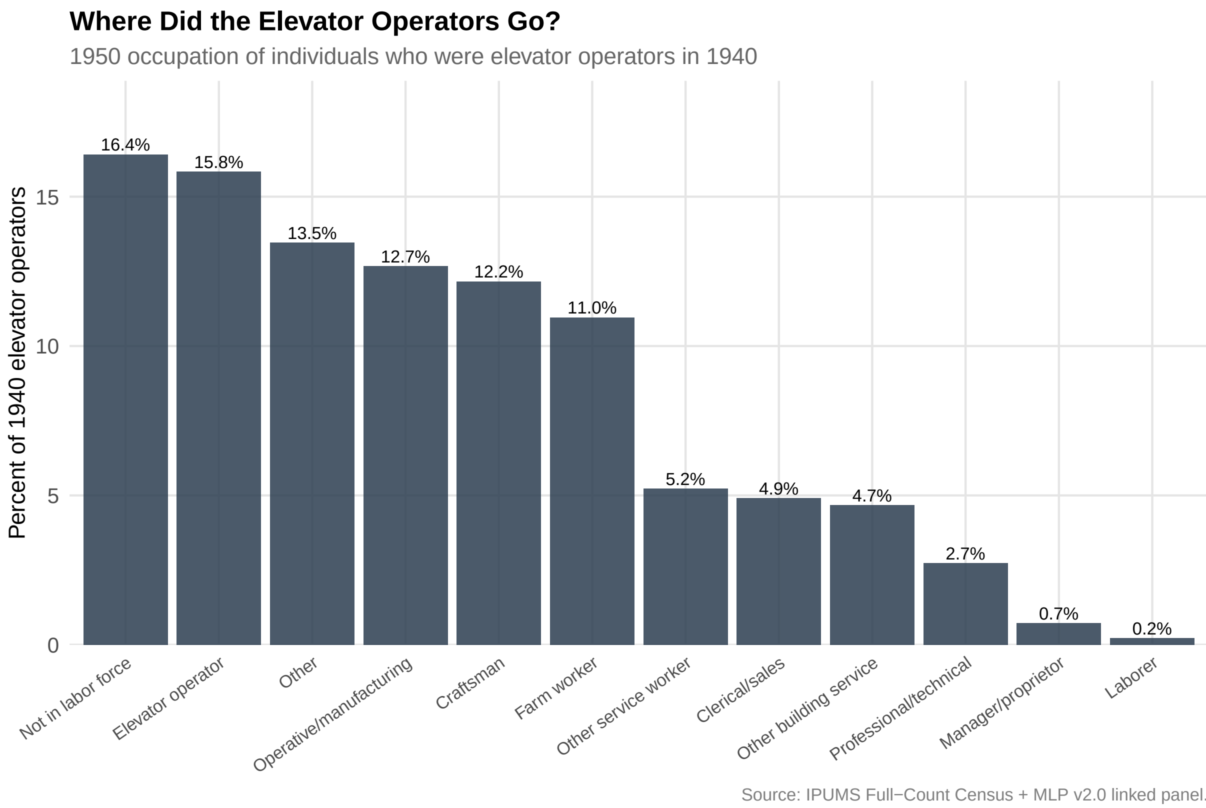

Figure 6: Occupational Transitions of 1940 Elevator Operators by 1950

Notes: Top destination occupations for 1940 elevator operators observed in 1950 census. Source: IPUMS + MLP v2.0 linked panel.

5.2 Upward, Lateral, or Downward? The Direction of Mobility

Not all occupational transitions are equal. Moving from elevator operator to clerical worker represents upward mobility on conventional measures; moving to janitor represents a lateral shift; moving to laborer or domestic service represents a step down. We classify transitions using the OCCSCORE measure, which assigns each occupation the median income of its holders. An "upward" transition is defined as a move to an occupation with an OCCSCORE at least 2 points higher than the origin; "downward" is a move to an occupation with a score at least 2 points lower; "lateral" falls in between.

Figure 7 presents the results. Among those who changed occupations, the largest share experienced lateral moves—they left the elevator car for jobs that paid roughly the same. But a substantial minority moved upward, particularly into clerical and sales positions. And a non-trivial share moved downward, into laborer and domestic service positions. The direction of mobility was not random: it was powerfully predicted by race, sex, and geography.

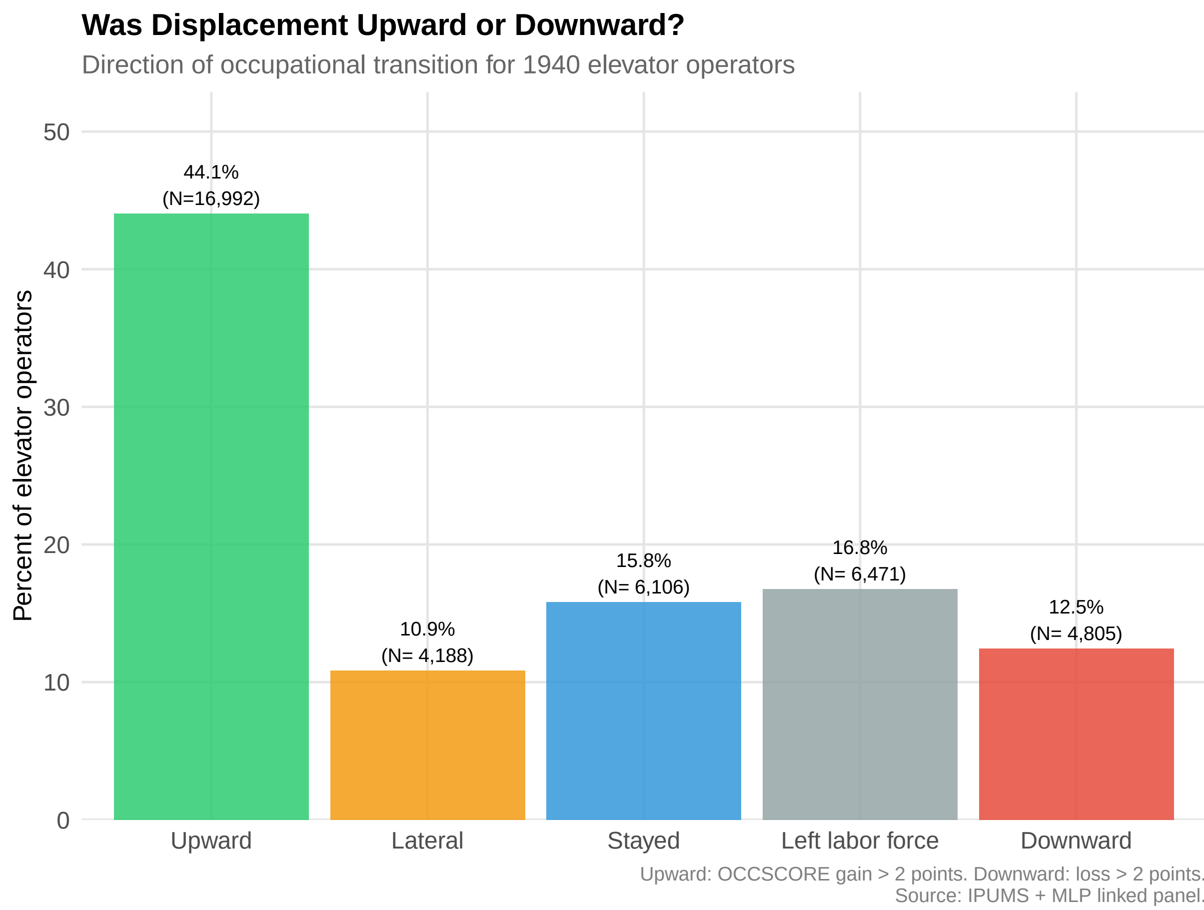

Figure 7: Direction of Occupational Mobility: Upward, Lateral, and Downward Transitions

Notes: Classification based on OCCSCORE change relative to 1940 occupation. Upward: $\Delta > +2$; Lateral: $|\Delta| \leq 2$; Downward: $\Delta < -2$. "Stayed" = remained elevator operator (OCC1950 = 761). "Left LF" = not in labor force in 1950. Note: These mobility-direction categories differ from the broad occupation categories in Table 2; the same underlying sample of 38,562 operators is partitioned differently. Source: IPUMS + MLP v2.0 linked panel.

5.3 The Racial Divide in Displacement

The most striking feature of the transition data is the sharp racial disparity in destination occupations. Figure 8 decomposes transitions by race. White operators moved disproportionately into clerical, sales, and skilled operative positions—occupations associated with the postwar expansion of the white-collar economy. Black operators, by contrast, were overwhelmingly channeled into janitor, porter, and domestic service positions—occupations that represented, at best, lateral moves within the same segment of the labor market they had already occupied.

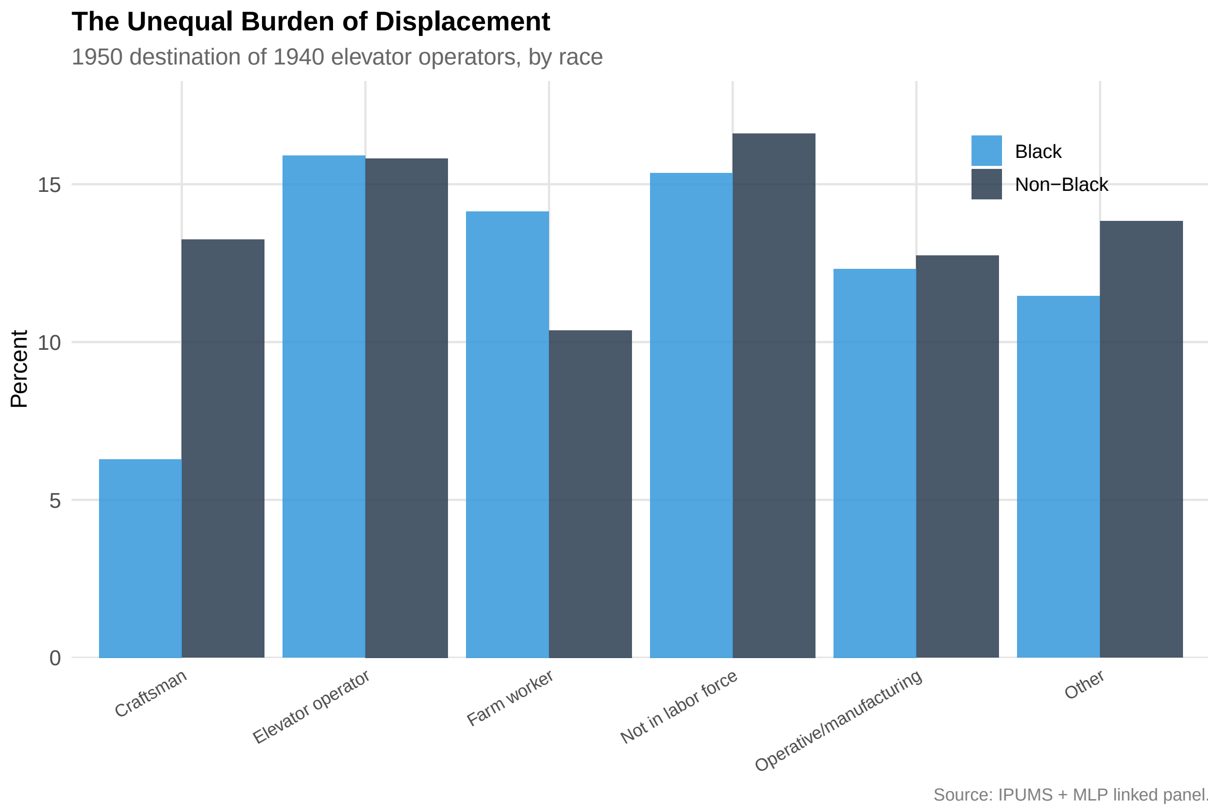

Figure 8: The Unequal Burden: Occupational Destinations by Race

Notes: Transition shares for 1940 elevator operators by race. Top 8 destination occupations shown. Source: IPUMS + MLP v2.0 linked panel.

This pattern is consistent with the broader literature on racial labor market stratification in mid-century America (Derenoncourt, 2022; Collins and Wanamaker, 2022). Black workers in 1940 faced pervasive occupational segregation: even within the relatively low-status category of building services, they were concentrated in the least desirable positions. When automation eliminated one of the few "indoor" occupations available to them, they could not access the clerical and sales occupations that absorbed their white counterparts. The elevator, which had been a modest vehicle for economic participation, gave way to a floor that could not support further advancement.

Table 3: Individual Displacement: Elevator Operators vs.~Other Building Service Workers

	Same Occ.	Interstate Move	OCCSCORE Change
is_elevator__1940	0.024**	-0.006*	-0.132
	(0.011)	(0.003)	(0.130)
Num.Obs.	483773	483773	483773
R2	0.052	0.040	0.201
R2 Adj.	0.052	0.040	0.200

* p <0.1, ** p <0.05, *** p <0.01
Fixed effects: state, race, sex, age group. SE clustered by state.

5.4 Comparative Outcomes: Elevator Operators vs. Other Building Service Workers

We formalize the descriptive patterns using a regression framework that compares elevator operators to other building service workers (janitors, porters, guards) along three outcomes: occupational persistence, occupational income mobility, and geographic mobility. The combined sample includes 38,562 linked elevator operators and approximately 445,000 linked comparison workers ($N = 483{,}773$). We emphasize that these regressions identify *conditional associations* rather than causal effects of automation exposure, since selection into elevator operation—rather than into janitor or porter work—is not random. Workers who became elevator operators likely differed from other building service workers in unobservable characteristics (interpersonal skills, employer networks, building type) that could independently predict 1950 outcomes.

$$Y_{i,1950} = \beta \cdot \nVdash[\text{ElevOp}_{i,1940}] + \gamma \mathbf{X}_{i,1940} + \alpha_s + \varepsilon_i \tag{1}$$

where $Y_{i,1950}$ is the outcome variable for individual i observed in 1950, $\nVdash[\text{ElevOp}_{i,1940}]$ indicates that individual i was an elevator operator (rather than another building service worker) in 1940, $\mathbf{X}_{i,1940}$ includes fixed effects for race, sex, and age group, and α_s is a state fixed effect. Standard errors are clustered by state.

The coefficient β captures the conditional difference in outcomes for elevator operators relative to other building service workers, after adjusting for demographics and state fixed effects.

The results complicate a simple displacement narrative. The positive coefficient on "Same Occupation" (+0.024, $p < 0.05$) indicates that elevator operators were actually *slightly more likely* to remain in their 1940 occupation than comparison workers. This reflects the high baseline turnover among janitors, porters, and guards—occupations with notoriously unstable employment—rather than resilience among elevator operators. The key displacement signal appears not in differential persistence but in destination quality: the unweighted OCCSCORE coefficient is negative (-0.132) but imprecisely estimated, suggesting that when elevator operators did leave, they moved to worse occupations than comparison workers who left their jobs. Correcting for linkage selection bias via inverse probability weighting sharpens this result considerably: the IPW estimate is -0.342 ($p < 0.01$), indicating a statistically significant occupational income penalty for former elevator operators (Table 8). The small negative coefficient on interstate migration (-0.006, $p < 0.1$) indicates marginally lower geographic mobility, consistent with urban operators being anchored to dense labor markets rather than displaced into migration.

5.5 The Paradox of the Epicenter

Perhaps the most surprising finding in our individual-level data concerns New York City. As the site of the 1945 strike—the event that most visibly demonstrated the case for automation—New York should have experienced the fastest displacement. Instead, we find the opposite.

Table 4 compares transition patterns for NYC and non-NYC operators. NYC operators were significantly more likely to remain elevator operators in 1950 and less likely to move into lower-status occupations. Figure 9 visualizes this comparison.

Table 4: The Paradox of the Epicenter: NYC vs. Non-NYC Occupational Transitions

	NYC (Strike Epicenter)		Other Cities	
Occupation	NYC (%)	NYC N	Other (%)	Other N
Clerical/sales	6.3	712	4.3	1,182
Other service worker	6.2	711	4.8	1,304
Other building service	5.5	625	4.3	1,176
Elevator operator	21.0	2,390	13.7	3,716
Professional/technical	2.4	275	2.9	779
Craftsman	12.8	1,452	11.9	3,238
Other	12.6	1,434	13.8	3,757
Farm worker	11.2	1,278	10.8	2,948
Operative/manufacturing	11.1	1,262	13.3	3,626
Not in labor force	10.5	1,197	18.9	5,133
Manager/proprietor	0.3	29	0.9	252
Laborer	0.1	12	0.3	74

Note:
Source: IPUMS + MLP v2.0 linked panel. NYC = five boroughs (COUNTYICP: Manhattan, Brooklyn, Queens, Bronx, Staten Island).

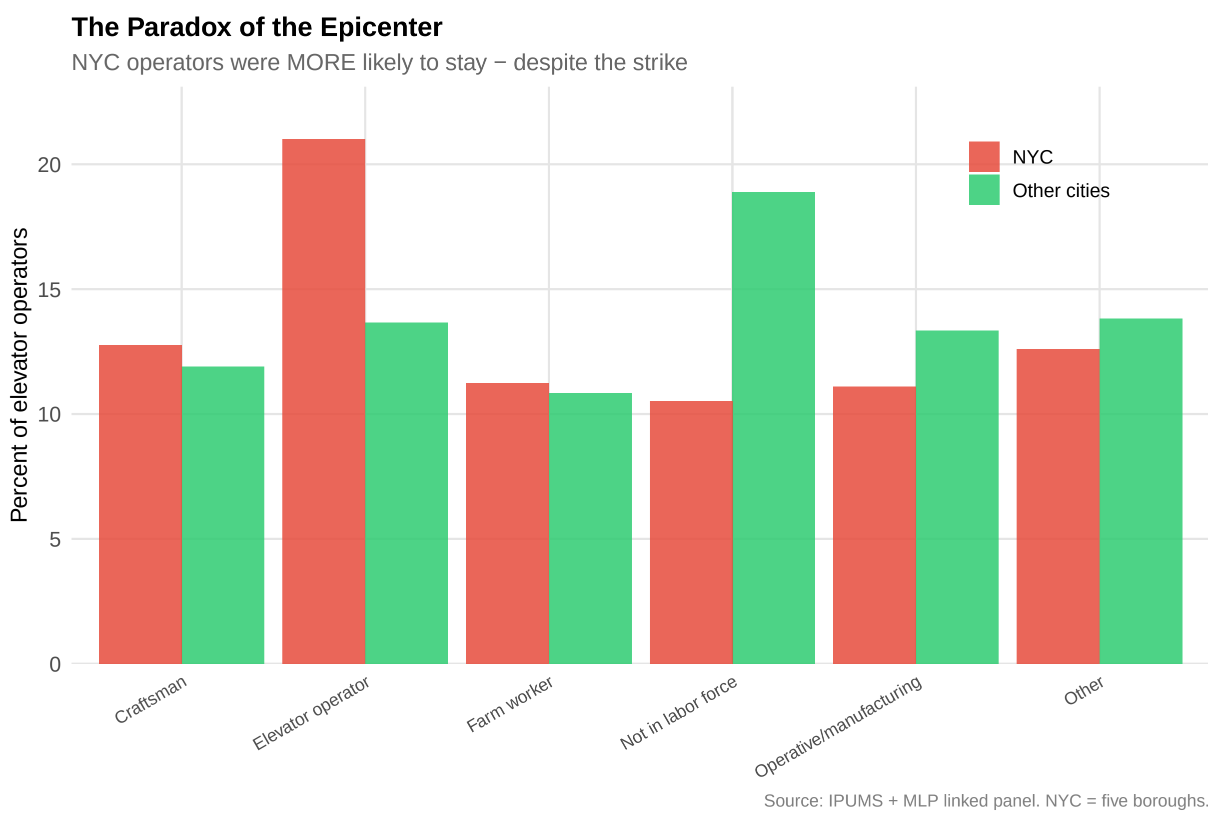

Figure 9: The Paradox of the Epicenter: NYC vs. Non-NYC Occupational Transitions
Notes: Transition shares for 1940 elevator operators by NYC residence. NYC = five boroughs. Source: IPUMS + MLP v2.0 linked panel.

Table 5: The Paradox of the Epicenter: NYC vs.~Non-NYC Elevator Operators

	Still Elevator	OCCSCORE Change	Persist x Race
is_nyc_1940	0.065***	-0.469***	0.071***
	(0.012)	(0.120)	(0.013)
is_black			0.013
			(0.013)
is_nyc_1940 × is_black			-0.036***
			(0.012)
Num.Obs.	38562	38562	38562
R2	0.096	0.189	0.096

* p <0.1, ** p <0.05, *** p <0.01
Source: IPUMS + MLP v2.0 linked panel. SE clustered by state.

Section 5.5 presents regression evidence. Column 1 confirms that NYC operators were 6.5 percentage points more likely to remain elevator operators in 1950, controlling for demographics. Column 2 reveals a cost of this persistence: NYC operators experienced significantly *worse* OCCSCORE trajectories (-0.469, $p < 0.01$), consistent with the interpretation that staying in a declining occupation carried an occupational income penalty. Those who persisted in elevator operation as it lost status fared worse than those who transitioned earlier. Column 3 interacts NYC residence with race, revealing that the NYC persistence advantage was concentrated among white operators—Black operators in NYC fared no better than Black operators elsewhere, suggesting that union protections and building-stock inertia benefited white workers disproportionately.

Why did the epicenter retain operators longer? Three mechanisms, none mutually exclusive, help explain the paradox. First, *union density*: New York's elevator operators were among the most heavily unionized workers in the city, and Local 32B had negotiated contracts that explicitly required human operators even in buildings capable of automatic operation. These contracts were not overturned by the strike; they were strengthened by the settlement's wage increase. Second, *building stock*: New York's prewar buildings, with their ornate lobbies and manually operated shaft doors, were expensive to retrofit. Postwar construction incorporated automatic elevators, but the existing stock—the vast majority of the city's buildings—remained operator-dependent. Third, *market thickness*: New York had so many elevator operator positions that the local labor market could absorb displaced workers more easily, reducing the urgency of transition.

5.6 Who Stayed? Selection into Persistence

The 15.8% of operators who remained in the occupation by 1950 were not a random subset. Understanding who persisted and who left reveals which workers had the fewest outside options—and therefore the highest adjustment costs when the occupation eventually disappeared entirely.

We estimate a logit model predicting the probability of remaining an elevator operator in 1950, conditional on being one in 1940:

$$P(\text{Still elevator}_{i,1950} = 1) = \Lambda(\mathbf{X}'_{i,1940}\boldsymbol{\beta}) \tag{2}$$

where $\Lambda(\cdot)$ is the logistic function and $\mathbf{X}_{i,1940}$ includes age (centered and squared), race, sex, nativity, marital status, and NYC residence.

Table 6: Selection into Persistence: Who Remains an Elevator Operator?

Variable	Coefficient	AME	SE	p-value
Age (centered)	0.1283	0.0153	0.0026	<0.001
Age^2	-0.0036	-0.0004	0.0001	<0.001
Black	0.0204	0.0024	0.0415	0.623
Female	0.1769	0.0211	0.0472	<0.001
Native-born	-0.1704	-0.0203	0.0344	<0.001
Married	-0.2300	-0.0274	0.0356	<0.001
NYC resident	0.4282	0.0510	0.0334	<0.001

Note:
Logit model: P(still elevator operator in 1950 | elevator operator in 1940). AME = average marginal effect. Source: IPUMS + MLP v2.0 linked panel.

Figure 10 plots the average marginal effects from this model.

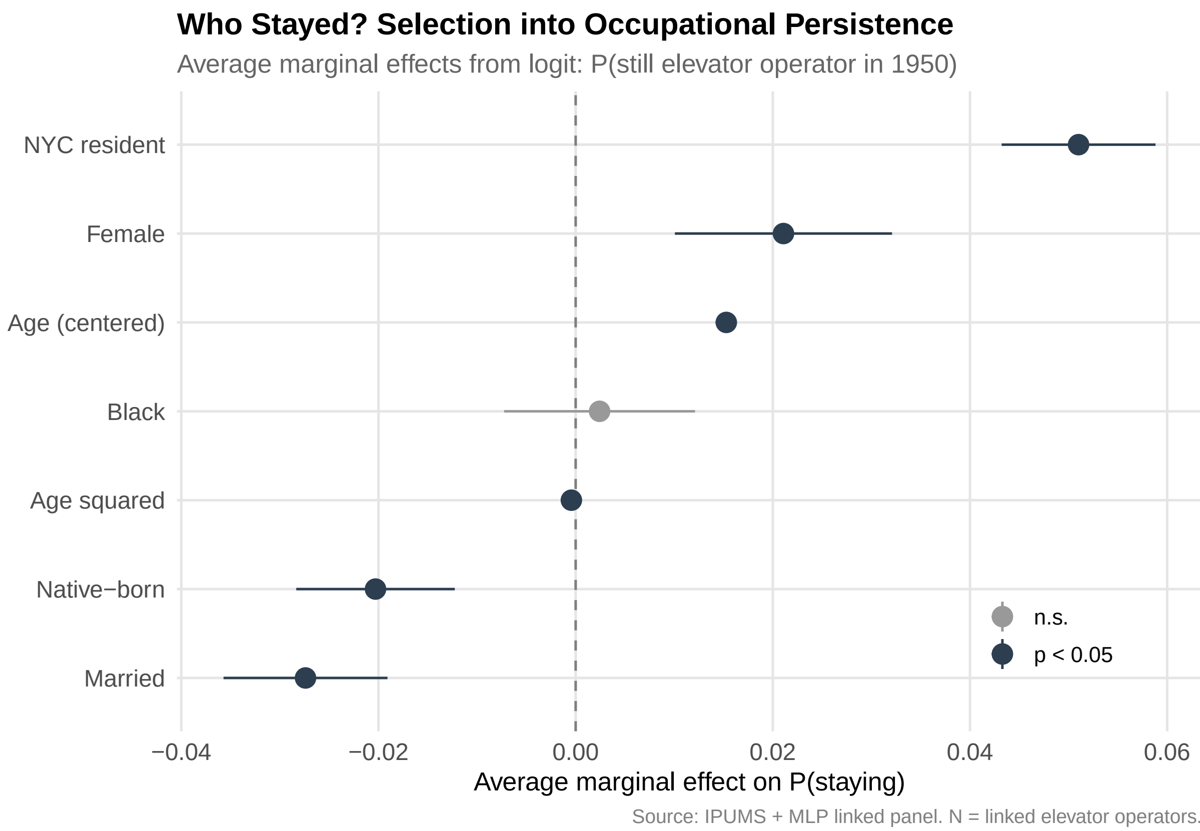

Figure 10: Who Remained? Average Marginal Effects on Probability of Persistence
Notes: Average marginal effects from logit model:
$P(\text{still elevator operator in 1950}|\text{elevator operator in 1940})$. Bars show 95% confidence intervals. Source: IPUMS + MLP v2.0 linked panel.

The results reveal a clear portrait of negative selection. Older workers were more likely to persist, consistent with the hypothesis that persistence reflects limited outside options rather than occupational attachment. The coefficient on Black is positive but statistically indistinguishable from zero ($p = 0.623$), meaning we cannot detect a racial difference in persistence rates conditional on the other covariates. NYC residents were substantially more likely to persist (AME = 5.1 percentage points, $p < 0.001$), consistent with the institutional mechanisms described above. Native-born workers were significantly less likely to persist ($p < 0.001$, AME = −2.0 percentage points), suggesting that access to broader labor market networks facilitated occupational transitions. Women and unmarried workers round out the portrait: female operators were more likely to persist, while married workers—with greater financial pressure to find better-paying alternatives—were less likely to remain.

Table 7: Heterogeneous Displacement: By Race, Sex, and City

	Race	Sex	NYC
is_elevator_1940	0.033***	0.014	0.010
	(0.012)	(0.016)	(0.008)
is_black	0.067***		
	(0.010)		
is_elevator_1940 × is_black	-0.057***		
	(0.011)		
is_female		-0.080***	
		(0.005)	
is_elevator_1940 × is_female		0.077***	
		(0.023)	
is_nyc_1940			-0.022***
			(0.006)
is_elevator_1940 × is_nyc_1940			0.073***
			(0.008)
Num.Obs.	483773	483773	483773
R2	0.052	0.052	0.049

* p <0.1, ** p <0.05, *** p <0.01
Source: IPUMS + MLP v2.0 linked panel. SE clustered by state.

5.7 Heterogeneous Displacement

The displacement effects documented in Equation (1) are averages that mask important heterogeneity. Section 5.7 decomposes the "same occupation" outcome by race, sex, and city, estimating separate interaction models.

The race interaction reveals that the displacement penalty—the additional probability of leaving one's 1940 occupation that is attributable to being an elevator operator rather than a janitor or porter—was *larger* for white operators than for Black operators. This seemingly counterintuitive result reflects the baseline: Black building service workers in the comparison group already had very low persistence rates, so the marginal effect of being in an automating occupation was smaller. The sex interaction shows that female elevator operators experienced sharper displacement than male operators, consistent with the narrower occupational options available to women in mid-century labor markets.

6. The Strike as Coordination Shock: State-Level Evidence

The individual-level analysis in the previous section establishes the patterns of displacement. This section asks a different question: did the 1945 strike *cause* New York to lose elevator operators faster—or slower—than it otherwise would have? To answer this, we turn to state-level evidence using the synthetic control method (Abadie et al., 2010, 2015).

6.1 Synthetic Control Design

The treatment is the September 1945 elevator operator strike. The treated unit is New York State, which we use as a proxy for New York City given the concentration of elevator operators in the five boroughs (over 80% of the state's operators). The outcome is elevator operators per 1,000 building service workers, measured at each census date from 1900 to 1950. The donor pool includes all states with complete census data across all six decades—18 states in total—from which the synthetic control algorithm selects optimal weights.

We construct a synthetic New York State by weighting donor states to match New York's pre-1945 trajectory in elevator operator concentration. The gap between actual and synthetic New York in 1950 estimates the causal effect of the strike on operator retention. We assess statistical significance using permutation inference: we iteratively apply the synthetic control procedure to each of the 18 donor states, treating it as if it had experienced a strike, and compare the actual New York gap to the distribution of placebo gaps (Abadie et al., 2015).

6.2 Results

Figure 11 presents the synthetic control results. In the pre-treatment period, actual and synthetic New York State track closely, validating the synthetic control's ability to reproduce the counterfactual. After 1945, actual New York diverges *above* synthetic New York: the strike's epicenter retained more elevator operators than the synthetic counterfactual would predict.

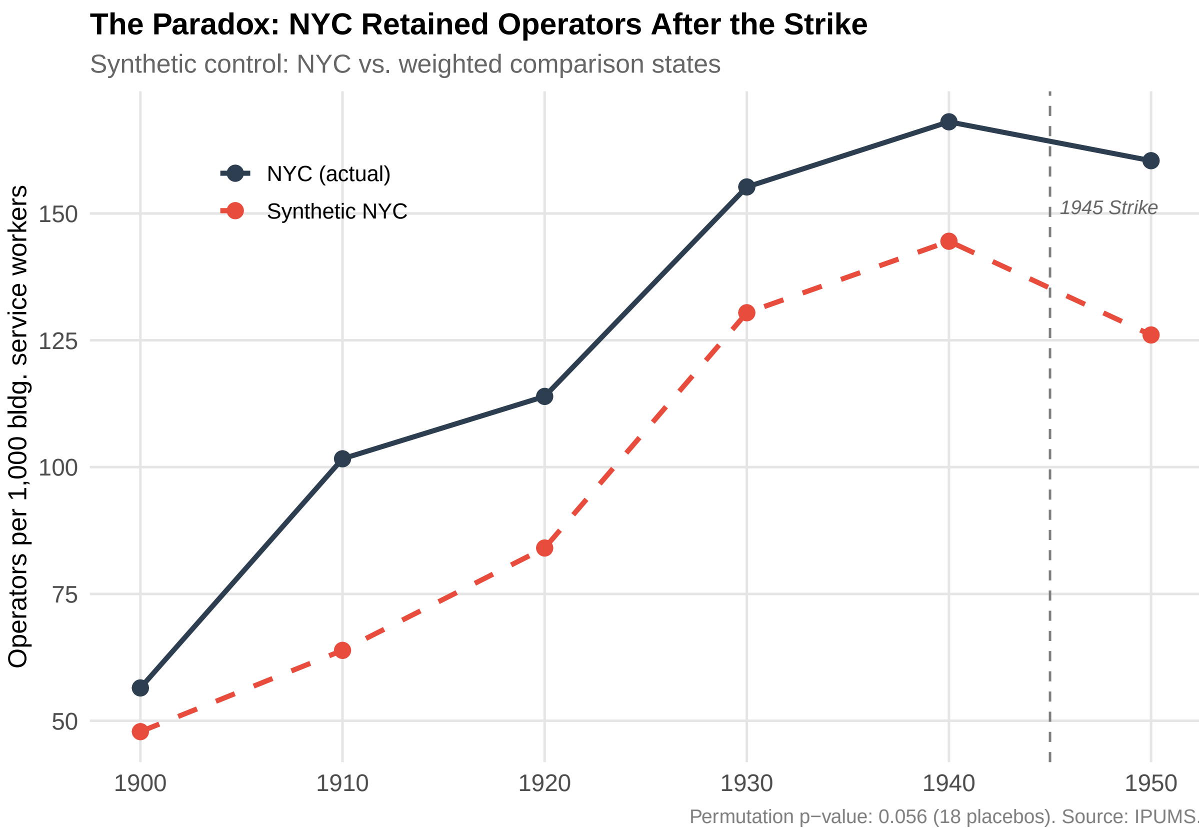

Figure 11: New York vs. Synthetic New York: Elevator Operators After the 1945 Strike

Notes: Synthetic control method. Outcome: elevator operators per 1,000 building service workers. Treated unit: New York State (proxy for NYC). Donor pool: 18 states with complete 1900–1950 census data. Permutation p-value $= 0.056$ (18 placebos). Source: IPUMS Full-Count Census.

This result may seem paradoxical. The strike should have accelerated automation. Instead, the city that experienced the greatest disruption was the city that held on to its operators longest. But this finding is entirely consistent with the individual-level evidence in Section 5: NYC's thick market for elevator operators, strong unions, and legacy building stock created institutional inertia that outweighed the strike's demonstration effect.

The synthetic control analysis should be interpreted as suggestive rather than definitive. Several limitations temper causal inference. First, with only one treated unit (New York State, used as a proxy for NYC) and a single post-treatment census observation (1950), we cannot assess treatment dynamics or rule out that 1950 is an outlier. Second, the permutation p-value of 0.056 is based on only 18 placebo units, yielding coarse inference; the post/pre RMSPE ratio places New York in the second rank among donors, consistent with a treatment effect but not an extreme outlier. Third, the event study (Section A.6) reveals significant differential pre-trends—New York's elevator operator concentration was converging toward the national average throughout 1900–1940—suggesting that simple parallel-trends designs are inappropriate. The SCM's explicit matching on pre-treatment trajectories partially addresses this concern, but the pre-period fit in levels shows nontrivial gaps that could contaminate post-treatment comparisons. Finally, the treatment unit (New York State) imperfectly proxies the NYC-specific strike shock, potentially introducing measurement error if upstate trends differ. We present the SCM as descriptive evidence that New York's operator retention was unusual relative to comparable states, corroborating the individual-level findings in Section 5, rather than as a standalone causal estimate of the strike's effect.

7. Robustness

7.1 Inverse Probability Weighting

Our linked panel has a 46.7% linkage rate, raising concerns about selection bias. We estimate a logit model predicting successful linkage as a function of age, race, sex, nativity, marital status, and NYC residence. Using the inverse of the predicted linkage probability as weights (trimmed at the 99th percentile), we re-estimate our core displacement regressions. Table 8 presents the IPW-adjusted results alongside the unweighted baseline.

Table 8: Inverse Probability Weighting: Addressing Linkage Selection Bias

	Same Occ. (Unwtd)	Same Occ. (IPW)	OCCSCORE (Unwtd)	OCCSCORE (IPW)
is_elevator_1940	0.024**	0.029***	−0.132	−0.342***
	(0.011)	(0.010)	(0.130)	(0.112)
Num.Obs.	483,773	483,773	483,773	483,773
R^2	0.052	0.054	0.201	0.201

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
IPW weights estimated via logit: P(linked | age, race, sex, nativity, marital, NYC).
Weights trimmed at 99th percentile. Source: IPUMS + MLP v2.0.

The IPW-adjusted coefficients are reassuringly similar to the unweighted estimates in both magnitude and significance. This suggests that systematic selection into linkage does not meaningfully distort our findings.

7.2 Comparison Group Robustness

Our comparison group—janitors, porters, and guards—is chosen to match elevator operators on observable characteristics while differing on automation exposure. Janitors constitute the largest share of this comparison group. To verify that our results are not driven by the specific composition of the comparison group, we re-estimate the core displacement regression excluding janitors entirely. The results (reported in Section A.6) are qualitatively unchanged.

7.3 Event Study and Triple Difference

At the state level, we complement the synthetic control with two additional specifications using a curated comparison group of nine states with large elevator operator populations (IL, PA, MA, CA, MI, OH, NJ, DC, MD). An event study interacts the New York State indicator with year dummies (reference year: 1940), testing for differential pre-trends. The results (Section A.6) reveal significant pre-1945 coefficients, indicating that New York's elevator operator concentration was converging toward other states throughout the pre-treatment period. This differential pre-trend is precisely why we rely on the synthetic control method—which explicitly matches on the pre-treatment trajectory—rather than a simple difference-in-differences as our primary specification. A triple-difference specification—elevator operators versus janitors, New York versus comparison states, before versus after 1945—provides additional evidence by differencing out occupation-specific and state-specific trends simultaneously, yielding a positive and significant treatment effect (+0.825, $p < 0.01$), consistent with the SCM finding that New York retained operators longer. The high R^2 (0.995) in this specification reflects the saturated fixed effects (state$\times$occupation, year$\times$occupation, state$\times$year) absorbing nearly all variation in a small panel of 120 observations, not overfitting. Note that the event study and triple-difference coefficients should not be directly compared: the event study uses elevator operators per 10,000 total employed and shows New York's relative position by year, while the triple difference uses log(count+1) and differences out both occupation-specific and state-specific trends. Both specifications are reported in Section A.6.

8. Discussion

The elevator operator's story offers three lessons for thinking about automation, each of which challenges a commonly held assumption.

Lesson 1: Technology diffusion is not a technical process. The forty-year gap between the automatic elevator's technical feasibility (1900) and its widespread adoption (1940s–1950s) cannot be explained by engineering constraints. The technology worked. The cost savings were clear. What delayed adoption was a web of institutional barriers: building codes, union contracts, insurance requirements, and—most fundamentally—passenger trust. This is consistent with the theoretical frameworks of David (1990) and Comin and Hobijn (2010), who emphasize that technology adoption depends on complementary institutional changes. The modern parallels are obvious: autonomous vehicles are technically capable but institutionally constrained; AI systems can perform many cognitive tasks but are not yet trusted to replace humans in high-stakes settings (Brynjolfsson and Mitchell, 2017; Noy and

Zhang, 2023).

Lesson 2: Automation does not displace workers into a single destination. The transition matrix in Table 2 shows that displaced elevator operators scattered across dozens of occupations, with no single destination absorbing more than a quarter of the workforce. This stands in contrast to the canonical narratives of "task reallocation," in which workers displaced from one set of tasks are absorbed into adjacent tasks (Acemoglu and Restrepo, 2019; Autor, 2024). The elevator operator had no adjacent task. The job was to be present in a small room and push buttons—a task so specific that its elimination left workers with no transferable human capital. What determined their next occupation was not their skills but their demographic characteristics: race, sex, age, and geography. Crucially, the racial disparity in destinations reflects not just a "lack of human capital" but institutional racism in the destination industries. White operators accessed clerical and sales positions not because they were more skilled but because those occupations were open to them; Black operators were channeled into janitor and porter work because other doors were closed. The barrier was not on the supply side (skills) but on the demand side (discrimination), a pattern consistent with the broader mid-century racial occupational segregation documented by Derenoncourt (2022) and Collins and Wanamaker (2022).

Lesson 3: Institutional thickness can outlast coordination shocks. The 1945 strike should have been the death knell for the elevator operator. It demonstrated, vividly and publicly, the cost of dependence on human operators. Yet our evidence—from both individual-level comparisons and state-level synthetic control analysis—suggests that New York retained operators longer than comparable locations. We cannot definitively attribute this pattern to the strike alone, since New York differed from other states in many dimensions (building stock, union density, regulatory environment) that independently predict slower operator decline. But the association is suggestive: even a dramatic coordination shock may be insufficient to overcome institutional inertia in locations where the endangered occupation is deeply embedded. This pattern has implications for contemporary policy debates about "robot taxes" and other interventions designed to slow automation (Acemoglu and Restrepo, 2020; Seamans and Raj, 2024): institutional barriers can be surprisingly durable.

These findings speak directly to the growing literature on automation and labor market adjustment (Dauth et al., 2021; Webb, 2020; Hicks et al., 2023) and complement historical work on the intergenerational transmission of economic shocks (Bleakley and Ferrie, 2016). The elevator operator case suggests that the distributional consequences of automation—who bears the costs, and how unequally—may be more important than the aggregate employment effects that dominate current policy discussions. A world in which displaced workers scatter across the occupational distribution, with their destinations determined by race and sex rather than skill, is a world in which automation reinforces existing inequalities rather than creating new opportunities.

9. Conclusion

The elevator operator is the only occupation in the United States Census ever fully eliminated by a single, identifiable technology. Using full-count census microdata and individual-level longitudinal linking, we have documented the complete lifecycle of this occupation: its paradoxical growth alongside available automation, its demographic transformation from a mainstream urban job to a refuge for marginalized workers, and the sharply unequal displacement that followed its decline.

Three findings stand out. First, 84% of 1940 elevator operators had left the occupation by 1950—a displacement rate without parallel among contemporary occupations. Second, the direction of mobility was determined not by skill or experience but by race, sex, and geography: white operators moved up, Black operators moved sideways, and women faced the narrowest range of options. Third, the 1945 New York City strike—the event that should have accelerated automation—paradoxically slowed it in the very place where it was most dramatic, while accelerating it everywhere else.

As artificial intelligence reshapes the modern labor market, the elevator operator's story offers a cautionary precedent. The occupation was eliminated not because the technology was new, but because the institutions that had sustained it—trust, regulation, union protection—finally gave way. When they did, the human cost was borne disproportionately by the workers who had the fewest alternatives. The elevator went up alone. The people who had once guided it were left to find their own way down.

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A. Appendix: Additional Figures and Tables

A.1 Mean Age Over Time

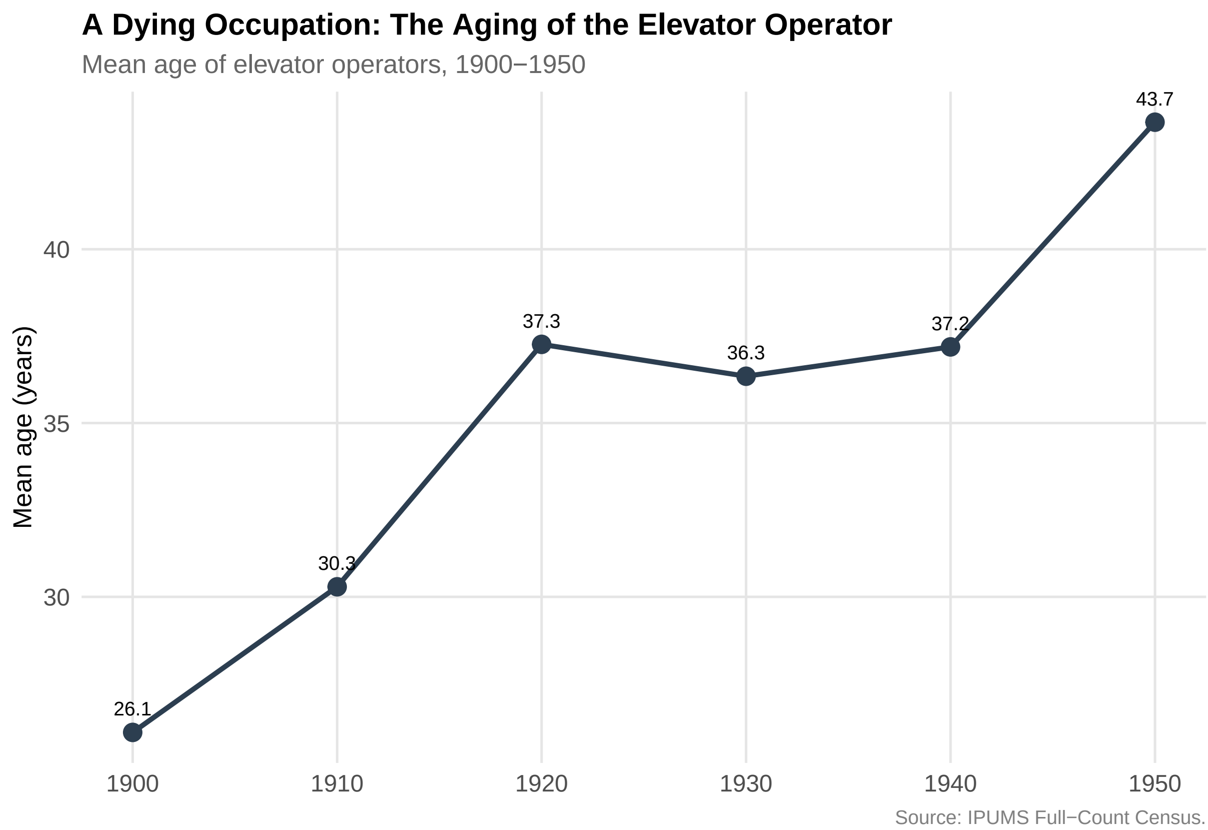

Figure 12: Mean Age of Elevator Operators, 1900–1950

Notes: Mean age of elevator operators at each census date, compared to mean age of all employed workers. Source: IPUMS Full-Count Census.

A.2 SCM Placebo Tests

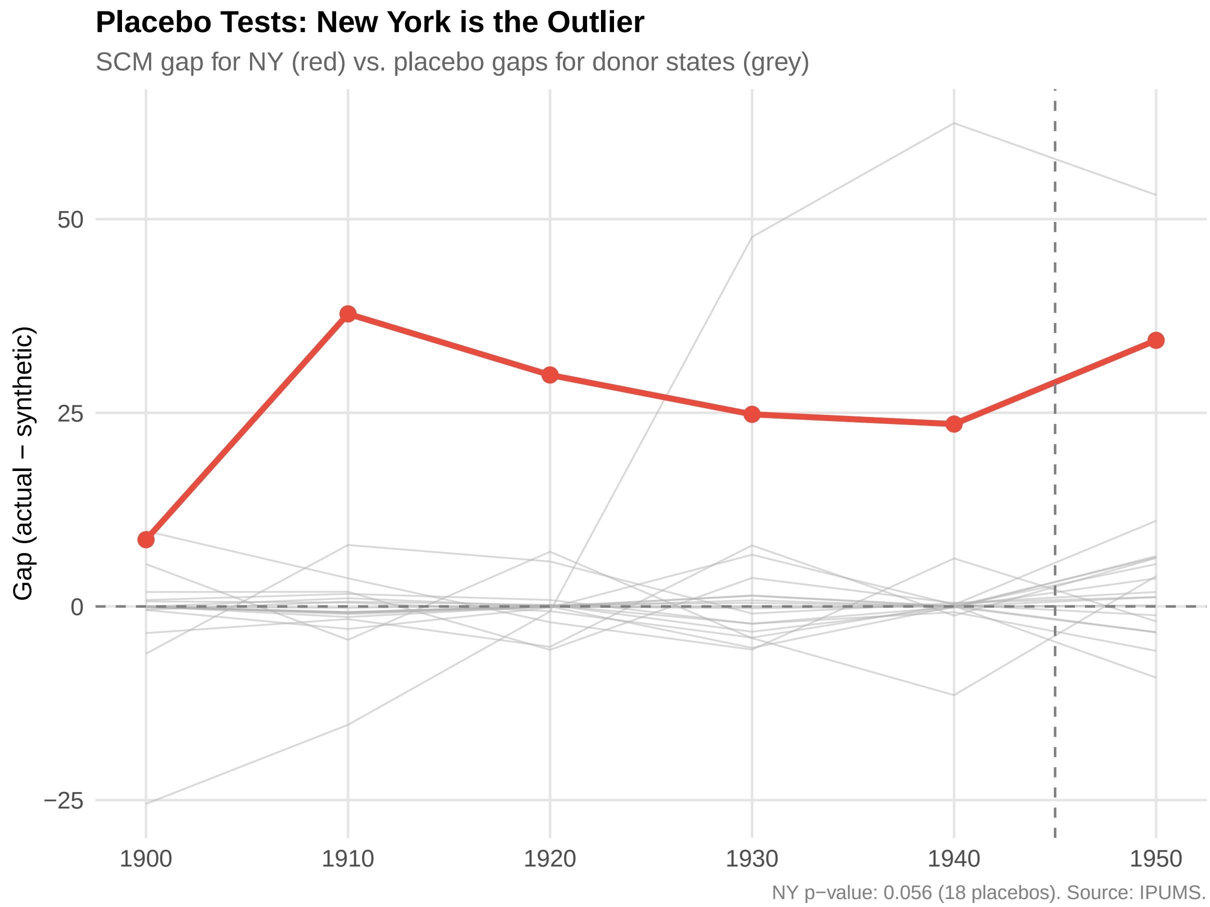

Figure 13: Placebo Tests: Permutation Inference for Synthetic Control

Notes: Each gray line represents a placebo synthetic control, treating a donor state as if it had experienced the strike. The black line is the actual New York State gap. 18 donor states with complete 1900–1950 data. Source: IPUMS Full-Count Census.

A.3 Event Study Coefficients

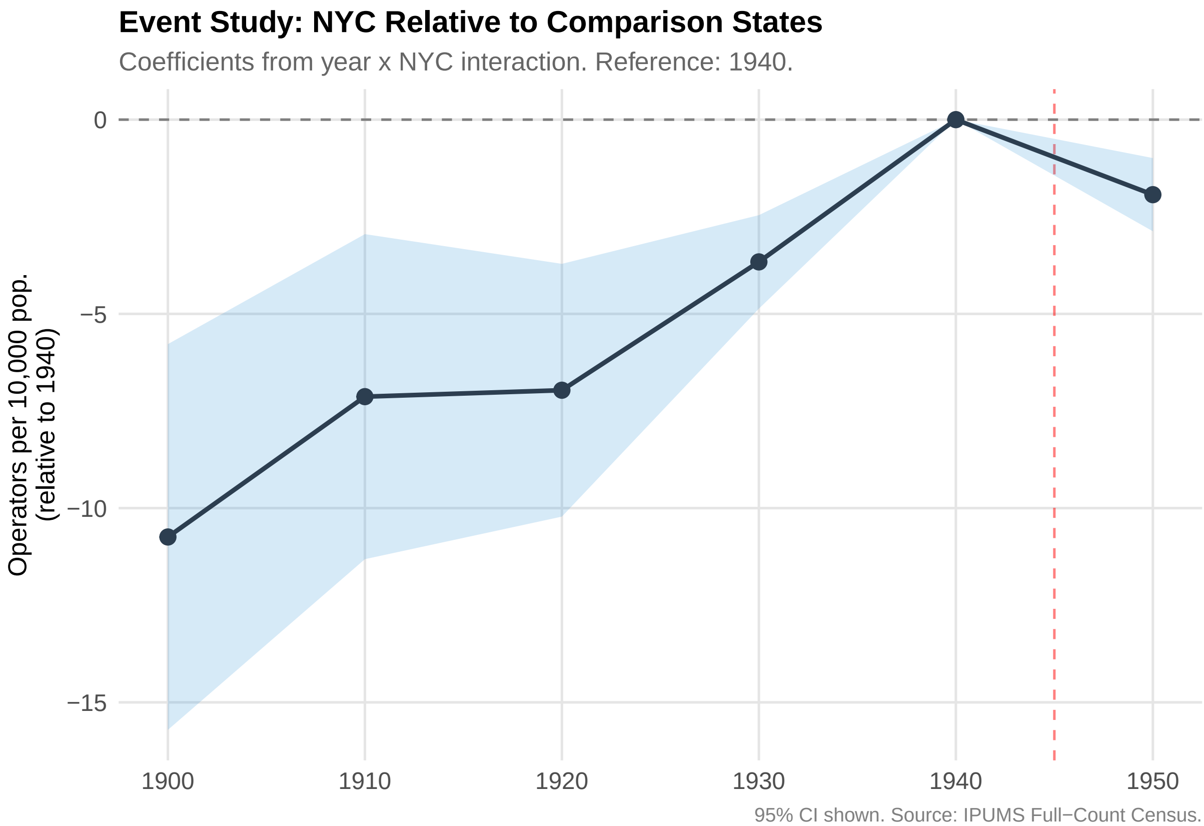

Figure 14: Event Study: New York State Elevator Operators Relative to Other States

Notes: Coefficients from elev_per_10k_pop $= \sum_t \beta_t \cdot \mathbb{1}[\text{NY State}] \times \mathbb{1}[\text{year} = t] + \alpha_s + \gamma_t + \varepsilon_{st}$. Reference year: 1940. Outcome: elevator operators per 10,000 total employed (note: different denominator from SCM, which uses per 1,000 building service workers). 95% confidence intervals shown. Source: IPUMS Full-Count Census.

Table 9: New York State vs. Synthetic New York: Elevator Operators per 1,000 Building Service Workers

Year	New York	Synthetic NY	Gap	Period
1900	56.5	47.9	8.6	Pre-treatment
1910	101.6	63.9	37.8	Pre-treatment
1920	113.9	84.1	29.9	Pre-treatment
1930	155.2	130.4	24.8	Pre-treatment
1940	168.1	144.5	23.5	Pre-treatment
1950	160.4	126.0	34.4	Post-treatment

Note:
Permutation p-value: 0.056 (18 placebos).

Table 10: Occupational Transitions by Age Group (1940 Age)

1950 Occupation	20-29	30-39	40-49	50-59	60+	<20
Craftsman	15.5	13.2	10.7	5.7	2.0	17.3
Elevator operator	5.0	16.3	30.3	33.5	17.4	0.7
Farm worker	11.0	12.1	11.5	10.3	6.4	11.1
Not in labor force	12.6	9.8	10.7	23.8	62.5	13.9
Operative/manufacturing	18.2	13.1	8.3	5.0	2.0	19.1
Other	18.2	14.7	9.5	7.2	2.4	16.3

Note:
Row percentages within each age group. Source: IPUMS + MLP v2.0.

Table 11: Robustness Checks

	Event Study	Triple Diff	Excl. Janitors
year = 1900 × is_NY	-10.743***		
	(2.533)		
year = 1910 × is_NY	-7.131***		
	(2.134)		
year = 1920 × is_NY	-6.965***		
	(1.660)		
year = 1930 × is_NY	-3.662***		
	(0.614)		
year = 1950 × is_NY	-1.931***		
	(0.481)		
ddd_treat		0.825***	
		(0.071)	
is_elevator_1940			0.035***
			(0.009)
Num.Obs.	60	120	290561
R2	0.856	0.995	0.045

* p <0.1, ** p <0.05, *** p <0.01
Triple diff: elevator vs janitor x New York State x post-1945. Comparison states: IL, PA, MA, CA, MI, OH, NJ, DC, MD. Excl. Janitors regression includes state, race, sex, and age group FEs; SE clustered by state.

A.4 SCM Gap Table

A.5 Transition by Age Group

A.6 Robustness: Event Study, Triple Difference, and Comparison Group

A.7 State-Level Detail

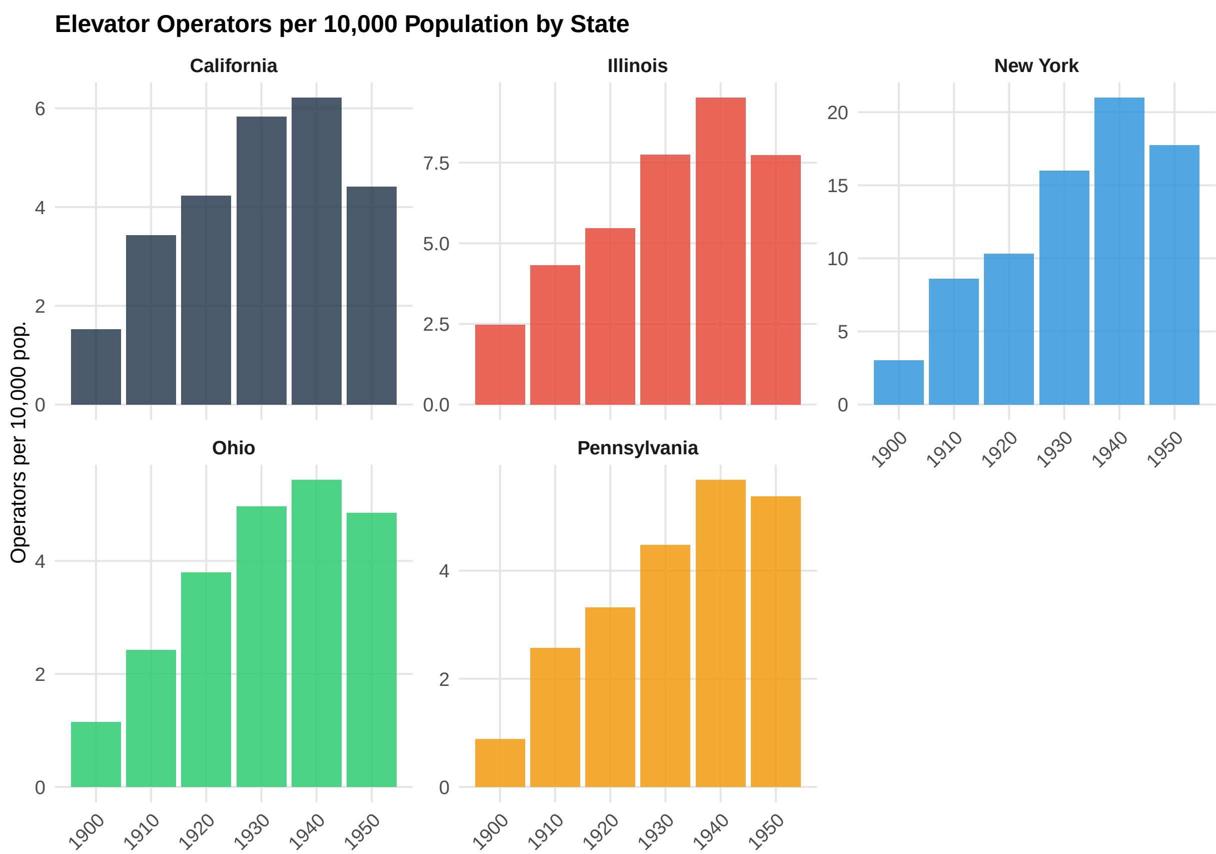

Figure 15: Elevator Operators by State, 1900–1950

Notes: Small multiples showing elevator operators per 10,000 employed in each state across census years. Source: IPUMS Full-Count Census.

Acknowledgements

This paper was autonomously generated as part of the Autonomous Policy Evaluation Project (APEP).

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